



Improving the representation of consumers' choice in transport within energy system models

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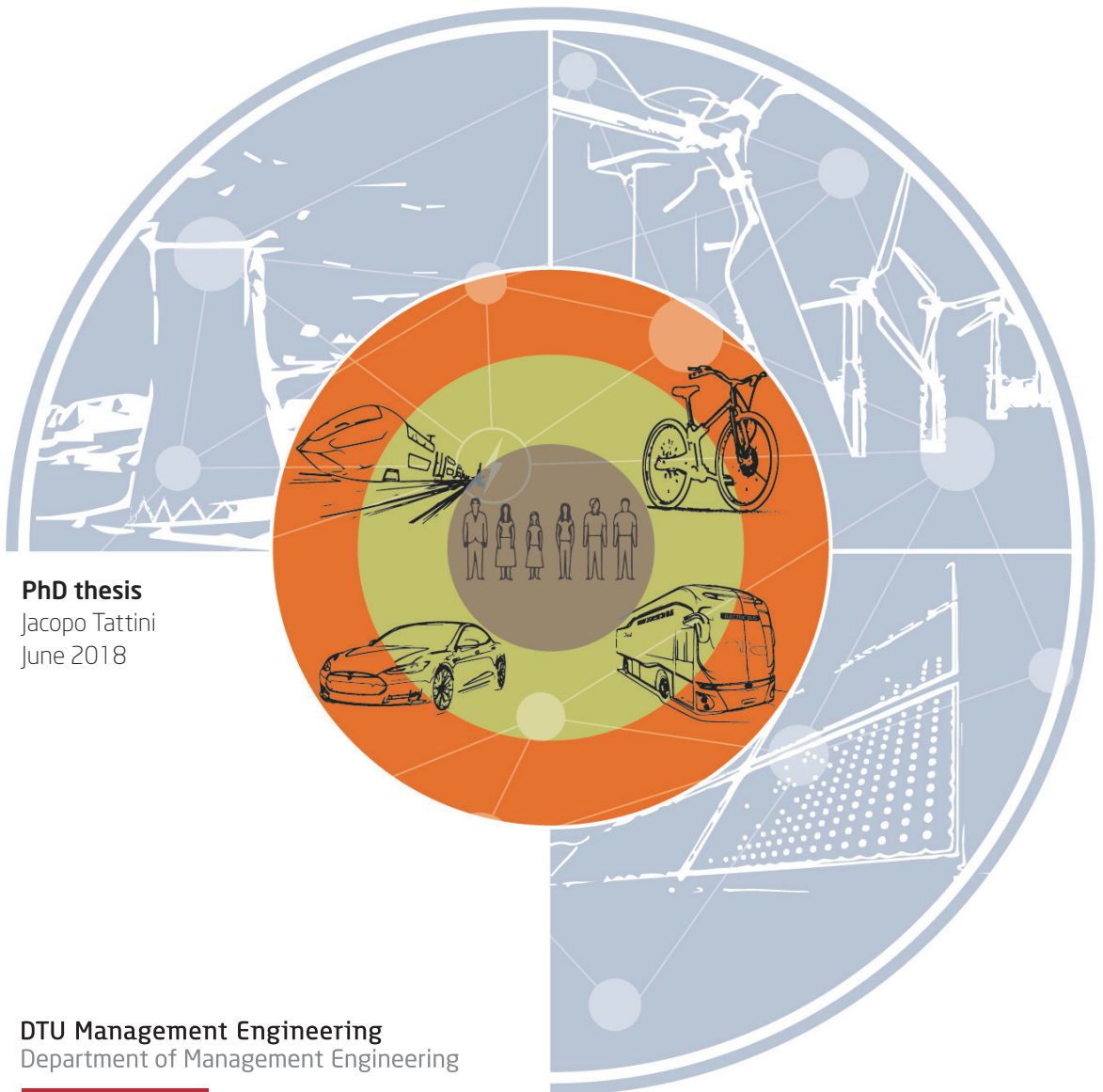
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Improving the representation of consumers' choice in transport within energy system models



PhD thesis

Jacopo Tattini
June 2018

TECHNICAL UNIVERSITY OF DENMARK

Management Engineering

System Analysis Division

Jacopo Tattini

**Improving the representation of consumers'
choice in transport within energy system
models**

Doctoral Thesis

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Lyngby, Denmark

June 2018

Abstract

Transport is a fundamental driver of economic development and a key supporter of welfare. Nonetheless, it is responsible for approximately 28% of global final energy use, 23% of the global energy-related CO₂ emissions and is regarded as the most complicated sector to decarbonise. In order to reduce the carbon intensity and energy consumption of the transportation sector, both technological and behavioural changes are required. Energy system models are a valuable tool for long-term energy planning. Decision makers have been using these models for more than three decades to explore alternative pathways towards greenhouse-gas (GHG) emissions free energy systems and to test the potential impact of policy measures. Bottom-up (BU) energy-economy-environment-engineering (E4) models in particular can provide a detailed technological representation of the energy system. However, these models are generally weak at representing human behaviour, despite it is a fundamental aspect of decision making in the transportation sector. This PhD thesis fills this gap by proposing several methodologies that improve the representation of consumers' choice in passenger transport within energy system models, thus paving the way for the possibility to carry out novel transport analyses and to consider a wider array of decarbonisation policies.

The first part of this thesis reviews the current scientific literature regarding integrated energy and transport models. It highlights the failing in representing consumers' decision making and identifies modal choice and vehicle choice as key behavioral features to be integrated in the modeling framework to overcome the existing limitation. Following these two findings, this thesis presents the methodologies developed within the scope of this PhD research to incorporate modal choice and vehicle choice in TIMES-DK, the TIMES model of the Danish energy system. The methodologies developed can be classified in two categories: those that extend the structure of the TIMES model to accommodate novel transport-specific variables and those that link the TIMES model with an external transport model. Thanks to the broad spectrum of approaches developed and tested within the scope of this PhD research, this thesis ultimately aims at acting as a guide for fellow researchers interested in including behavioural realism of transport users' choice in E4 models. The thesis describes how traditional limits in the representation of behaviour within BU optimization E4 models can be addressed with the different approaches developed. Then, it compares the various methodologies with respect to the capability to capture key behavioural features, to answer different policy questions and to the modeling efforts required to reproduce the models.

The novel methodologies proposed inaugurate the possibility to perform more comprehensive analyses of decarbonisation pathways, which include both the behavioural and technological dimension. The results of the PhD study indicate that modal shift potentially has a positive contribution to the decarbonisation of the energy system, helping to reach carbon-neutral energy system in Denmark in 2050 at faster pace and

with lower cumulative emissions. The analyses carried out within the scope of this PhD research find that car transport is likely to maintain the highest modal share also in the future, suggesting that modal shift should be accompanied by the electrification of the car sector to comply with the Danish environmental targets and overarching climate targets. The analyses are intended to inform Danish policy makers dealing with energy and transport planning on the beneficial contribution of modal shift and of the electrification of the car stock to reduce GHG emissions. The Nordic experience and the findings of the modeling analyses are used to give policy recommendations on the measures that the authorities should put in practice to encourage modal shift away from car to more sustainable modes of transport and to promote the deployment of electric cars. Finally, this PhD thesis discusses future research to address the remaining gaps concerning the representation of consumers' choice within BU optimization E4 models and suggests interesting energy and transport analyses that should be performed using the novel models hereby proposed.

Resume

Transport er en fundamental faktor for den økonomiske udvikling og en af hjørnestenene bag velfærd. Den er yderligt ansvarlig for 28% af det endelige energiforbrug og 23 % af alle energirelaterede CO₂ emissioner i verden, og anses som den sværeste sektor at dekarbonisere. For at kunne reducere karbonintensiteten og energiforbruget i transportsektoren er både teknologierne og forbrugsmønstre nødvendige at ændre. Energisystemmodeller er et værdifuldt værktøj for langsigtede energiplanlægning. Beslutningstagere verden over har brugt modeller i mere end tre årtier til at analysere alternative retningslinjer for drivhusgas frie energi systemer og til at teste politiske tiltag. Kategorien bottom-up energi-økonomi-miljø-ingeniørarbejde (E4) modeller står for en detaljeret repræsentation af energi systemet. Dog er disse modeller ofte svage til at repræsentere menneskelig adfærd, selvom det er et fundamentalt element for beslutningstagere i transportsektoren. Denne afhandling udfylder dette hul i energisystemmodeller gennem forskellige metoder, der kan repræsentere adfærd inden for transport sektoren, og fremviser dermed retningslinjer til udføre nye transportanalyser og politiske incitament strukturer.

Indledningsvist undersøger denne afhandling eksisterende videnskabelig litteratur inden for energi- og transportmodellering. Denne fremhæver manglende modellering af adfærdstendenser hos beslutningstagere og identificerer transportmiddelskift og køretøjs valg, som hovedpunkter, der skal integreres i modellerings værktøjer for at overkomme de eksisterende begrænsninger. Afhandlingen præsenterer metoder udviklet inden for rammerne af dette Ph.d. studie til at modellere transportmiddelskift og køretøjs valg i den danske TIMES energi systems model, TIMES-DK. De udviklede metoderne kan klassificeres i to underkategorier: værktøjer udviklet med henblik på blive inkorporeret i TIMES-DK med transportspecifikke variabler og de der forbinder TIMES-DK med en ekstern transport-model. Som følge af den omfattende udvikling og test af metoder i dette Ph.d. studie er målet, at afhandlingen skal bruges som en manual for kollegaer og forskere med interesse inden for E4 modeller og forbrugernes adfærdsmønstre i transport sektoren. Afhandlingen beskriver hvordan traditionelle E4 bottom-up optimerings modeller kan overkomme begrænsningerne takket være de udviklede værktøjer. Yderligere, sammenlignes metodernes evne til at skildre adfærdsmæssige hovedtræk med henblik på at besvare politiske spørgsmål og den krævende indsats for at reproducere modellen.

De nye metodiske værktøjer leder til en dybere og mere gennemgående analyse af fossil frie scenarier, hvor både adfærdsmønstre og teknologiske dimensioner er inkluderet. Resultatet af denne afhandling indikerer at transportmiddelskift potentielt har positiv indvirkning i at dekarbonisere energi systemet og hjælpe med at opnå en fossilfri energi sektor i Danmark inden 2050 og kan sænke dens kumulative CO₂ udledning. Undersøgelser udviklet i denne Ph.d.s anvendelsesområde bekræfter at forventes biler fortsat at være det førende transportmiddel i fremtiden. Et transportmiddelskift skal dog stadig suppleres med en

elektrificering af bil-sektoren for at sænke drivhusgas udledningen i henhold til de danske klima målsætninger. Analyserne har til formål at informere danske beslutningstagere om energi- og transportplanlægning om det fordelagtige bidrag fra modalskifte og elektrificering af bil-sektoren for at reducere drivhusgasemissionerne. De nordiske erfaringer og model analyser er brugt til at give politiske anbefalinger til incitamentstrukturer som beslutningstagere kan iværksætte i praksis for at opnå et transportmiddelskift væk fra konventionelle biler og til mere klimavenlige transportmidler og indfasning af elbiler. Til slut diskuterer denne Ph.d.-afhandling hvilke forskningsområder, inden for forbrugervalg i BU optimering E4 modeller, der er stadigvæk er svagt belyst og anbefaler interessante energi- og transportanalyser, der bør udføres ved at benytte de nye modeller, som er udviklet i denne Ph.d.-afhandling.

Acknowledgments

This PhD thesis marks the conclusion of my post-graduate studies and the very end of my education course, which I have started by studying management engineering, then moved to energy engineering, and finally specialized in energy system modeling and which has taken place in several countries worldwide. At the end of this three-year PhD research, I can finally claim (or maybe just pretend) to be an expert in the field of energy system modeling and energy and transport analysis.

Some tragic events that hit my family during my first year of PhD made me doubt about carrying on the PhD studies. Now that I am completing this course, I have primarily to thank my mother and my research team at DTU, particularly my supervisor, for having given me the time and the conditions to elaborate the bereavement, which allowed me to come back to the research activities with the proper mind-set.

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Έτσι, δεν γνωρίζω

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Contents

Abstract	1
Resume	3
Acknowledgments	5
1 Introduction	11
1.1 Background and motivation	11
1.2 Purpose of the thesis and research questions	12
1.3 Outline of the thesis	14
1.4 Publications	14
1.5 Timeline and role of collaborations	15
2 Literature review	17
2.1.1 Modal choice	18
2.1.2 Technology choice	19
3 Models and methodologies	21
3.1 The backbone model: TIMES-DK	22
3.1.1 TIMES model generator	22
3.1.2 Overview of TIMES-DK	22
3.1.3 Transportation sector in TIMES-DK	23
3.2 Representation of modal choice	24
3.2.1 TIMES-DKMS	24
3.2.2 MoCho-TIMES	25
3.2.3 TIMES-DKEMS	27
3.2.4 ABMoS-DK	28
3.3 Enhancements to vehicle choice representation	28
3.3.1 Consumer choice model	28
3.3.2 CarSTOCK model	29
3.4 Multi-model approaches	30
3.4.1 Soft-link of TIMES-DKMS and DCSM	30
3.4.2 Soft-link of ABMoS-DK and TIMES-DK	31
4 Analyses and main results	33

4.1	Potential contribution of modal shift to cut GHG emissions.....	33
4.2	Optimal level of shift away from car.....	35
4.3	Future composition of the car stock	36
4.4	Compliance of GHG emissions reduction pathways with a <2°C future	38
5	Policy implications and recommendations.....	41
5.1	Policies encouraging modal shift away from private cars	41
5.2	Policies promoting EV car uptake	42
5.2.1	Nordic experience on electric car uptake	42
5.2.2	Findings from modeling analyses.....	44
6	Discussion on modeling approaches	45
6.1	Features to incorporate behaviour in transport.....	46
6.1.1	Heterogeneity	46
6.1.2	Behavioural attributes.....	49
6.1.3	Tangible costs.....	51
6.1.4	Spatial dimension	51
6.1.5	Infrastructure capacity	53
6.1.6	Elastic transport demands.....	53
6.2	Models' capability to depict the behavioural features.....	54
6.3	Suitability to answer to policy questions.....	55
6.4	Modeling efforts, requirements and model reproducibility	60
6.4.1	Data	60
6.4.2	Softwares	62
6.4.3	Mathematical method	62
6.4.4	Soft linking.....	63
6.4.5	Model structure's complexity.....	63
6.4.6	Reproducibility and usability	64
7	Further research.....	67
7.1.1	Modeling	67
7.1.2	Analyses	68

8 Conclusions 71

References 73

Appendix 77

Abbreviations and units..... 253

1 Introduction

1.1 Background and motivation

Transport is a fundamental driver of economy and society and it plays a primary role in supporting economic growth and quality of life. However, transport is responsible for approximately 28% of total final energy use and for 23% of the world energy-related CO₂ emissions [1]. The International Energy Agency (IEA) estimates an increase of nearly 75% of global transport energy consumption by 2050 in its baseline scenario and almost a doubling of associated CO₂ emissions worldwide [2]. Transport is regarded as the most difficult sector to decarbonise, due to a variety of reasons. Its rate of growth of energy use and CO₂ emissions is 2% a year, the highest among all the end-use energy sectors. So far, the efforts to reduce transport GHG emissions by improving fuel economy standards have been offset by the increase of activity. Moreover, the global growth of transportation activity has been tracking that of GDP and is strongly linked to the increase of population and incomes [3]. Mobility demand per capita in non-OECD countries is still below the levels in OECD countries, but is expected to grow at fast pace. In addition, while several efficient and low-carbon technologies are available for the power and heat sectors, the transportation sector lags behind. Some low-carbon technologies have appeared in the market [4], but their high upfront costs still hamper a large-scale deployment, thus making policy support still a requirement to enhance their acceptability [5]. Moreover, the slow turnover rate of the existing vehicle stock and the lock-in effect originated by the existing infrastructure constitute additional barriers that slow down the deployment of new transportation technologies. Finally, technology development is only one of the levers to consider in relation to transport GHG emissions mitigation: technology adoption and usage are also key drivers of transportation sector's evolution, pointing to a need for behavioural analyses. To reduce transport externalities, the IEA suggests a combination of three technological and behavioural measures to promote concurrently: avoid travelling, shift to more efficient modes and improve vehicles' performances [2] [3]. Another set of measures recommended includes development of efficient technologies, changes in

pricing and budgeting, changing attitudes, infrastructure supply, innovative institutional arrangements and development of new methods [6].

Energy system models are valuable tools for long-term energy planning. Decision makers have been using them for more than three decades to identify resources and technology deployment pathways towards GHG emissions-free energy systems and to develop policy measures fulfilling the energy and emission targets [7 - 10]. Among energy system models, the category of BU E4 models (also called “techno-economic” models) stands for the detailed representation of the technological dimension and includes also the economic and environmental dimensions of the energy system. BU optimization E4 models are suitable to explore decarbonisation pathways considering cross-sectoral dynamics and synergies. On the other hand, these models are still weak at depicting human behavior that drives consumer’s choice [11 - 13]. However, individuals’ preferences and behavioural attitudes are a fundamental aspect of decision making in the end-use sectors (including transport).

1.2 Purpose of the thesis and research questions

The weak representation of consumers’ choice is widely considered one of the main limitations of BU optimization E4 models [14, 15], to the point that, to a certain extent, it has reduced their credibility for evaluating policies in the transportation sector. Integrating realistic consumers’ behaviour in transport within the model framework helps to identify the barriers limiting the adoption of more efficient modes of transport and the purchase of zero- and low-emission cars, and to understand which policies have greater impact towards such a transition. This thesis fills the gap concerning the weak representation of behavior in transport within BU optimization E4 models by developing and comparing diverse approaches to represent consumers’ decision making (such as modal choice and vehicle choice) in greater detail. The methodologies allow to potentially overcome one of the main limitations of BU optimization E4 models, making them more suitable for transport mitigation analysis. Furthermore, the methodologies developed within the scope of this PhD research inaugurate the possibility to assess policies affecting both technological development and consumers’ perceptions. Such novel approaches have been used to answer to innovative research questions (RQ) within the field of BU optimization E4 models. The RQs addressed with this PhD work can be classified in three categories: result-oriented, policy-oriented and modeling-oriented.

Result-oriented RQs:

- RQ 1.** *What is the potential contribution of modal shift to cut CO₂ emissions in Denmark?*
- RQ 2.** *What is the optimal level of shift away from car transport in Denmark?*
- RQ 3.** *Which groups of transport users are the most and least willing to shift away from car transport?*
- RQ 4.** *What is the future composition of the car stock in Denmark under different policy*

scenarios?

RQ 5. *Is the Danish decarbonisation target in line with a <2°C future?*

Policy-oriented RQs:

RQ 6. *What policies can encourage modal shift away from private cars?*

RQ 7. *What policies can assist in decarbonising the car sector?*

RQ 8. *How should cars' tax scheme be used to encourage the uptake of electric cars?*

Modeling-oriented RQs:

RQ 9. *What is state-of-the-art of the representation of modal and technology choice in integrated energy and transport models?*

RQ 10. *What features should be incorporated in E4 models to integrate realistic consumers' choice?*

RQ 11. *How easy is it to replicate the different models proposed?*

The overview of which paper answers to which RQ is provided in Table 1. The modeling-oriented RQs that are not addressed by any paper (i.e. RQ 10-11) are excluded from the table, but are answered in this thesis. Moreover, the paper describing the structure and usage of TIMES-DK is excluded from Table 1 since it does not answer to any of the RQs listed above, but only describes the backbone model used to implement the novel methodologies developed within this PhD research. Also the paper describing TIMES-DKEMS is excluded from the table since it is only dedicated to explaining the new methodology.¹

Table 1: Answers to RQs in the papers

	Literature review	TIMES-DKMS	MoCho-TIMES	ABMoS-DK	DCSM	Soft-link TIMES-DKMS and DCSM	NEVO 2018
RQ 1		✓	✓				
RQ 2		✓	✓				
RQ 3			✓	✓			
RQ 4		✓			✓	✓	
RQ 5						✓	
RQ 6		✓	✓	✓			
RQ 7					✓	✓	✓
RQ 8					✓		✓
RQ 9	✓						

Within this thesis, the answers to each of the RQs are not given in one unique section, rather they are presented in different sections throughout the thesis, depending on the category they belong to. Answers to result-oriented RQs are mostly given in Section 4, answers to policy-oriented RQs are primarily given in

¹ TIMES-DKEMS could be used to answer to RQ 1, RQ 2, RQ 5 and RQ 6

Section 5 and answers to modeling-oriented RQs are provided in Section 2 and 6. Every time a RQ is answered, an indication is given in the dedicated section.

1.3 Outline of the thesis

This thesis consists of two parts: the first part summarizes in a straightforward and organic way the entire work carried out during the PhD research, and the second part reports the publications relevant to this thesis. The first part of the thesis consists of seven sections besides the introduction. First, a review of the existing scientific literature on integrated energy and transport models is presented in Section 2. This highlights the limitation of traditional E4 models in representing consumers' choice realistically and suggests the integration of modal choice and vehicle choice in the modeling framework to overcome such weakness. Following these findings, Section 3 presents the methodologies developed to incorporate modal choice and vehicle choice in a BU optimization E4 model, specifically TIMES-DK, the TIMES model of the Danish energy system. Then, Section 4 summarizes the main results of the analyses carried out using the novel models. Section 5 uses such findings together with the lessons learned from the Nordic experience on electric car uptake to inform Danish policy makers on effective policy measures to foster modal shift from car transport to more sustainable modes of transport and to promote the deployment of electric cars. The discussion of the advantages and disadvantages of the different approaches is presented in Section 6, aiming at guiding fellow researchers in the selection of the most suitable modeling framework considering a wide range of criteria. Finally, Section 7 suggests the direction for further research and Section 8 presents the conclusions. In the second part of the thesis, an appendix presents the publications written during the PhD study period relevant to this thesis.

1.4 Publications

- I. **Literature review:** Venturini G.*, Tattini J.*, Mulholland E., Ó Gallachóir B. (2018). *Improvements in the representation of behaviour in integrated energy and transport models*, In press in *International Journal of Sustainable Transportation*, <https://doi.org/10.1080/15568318.2018.1466220>
- II. **The backbone model: TIMES-DK:** Balyk O., Andersen K., Gargiulo M., Karlsson K., Petrovic S., Tattini J., Venturini G., Dockweiler S., Næraa R., Termansen L. B. (2018). *TIMES-DK: technology-rich multi-sectoral optimisation model of the Danish energy system*, Accepted in *Energy Strategy Reviews*
- III. **TIMES-DKMS:** Tattini J., Gargiulo M., Karlsson K. (2018). *Reaching carbon neutral transport sector in Denmark – Evidence from the incorporation of modal shift into the TIMES energy system modeling framework*, *Energy Policy*, 113, 571-583
- IV. **MoCho-TIMES:** Tattini J., Ramea K., Gargiulo M., Yang C., Mulholland E., Yeh S., Karlsson K. (2018). *Improving the representation of modal choice into bottom-up optimization energy system models – The MoCho-TIMES mode*, *Applied Energy* 212, 265–282
- V. **TIMES-DKEMS:** Salvucci R., Tattini J., Gargiulo M., Karlsson K., *Modeling transport modal shift in TIMES models through elasticities of substitution*, In press in *Applied Energy*

- VI. **ABMoS-DK:** Ahanchian M., Gregg J., Tattini J., Karlsson K., *Analyzing effects of transport policies on travelers' behaviour for modal shift in Denmark*, Under review in *Case studies on Transport Policy*
- VII. **DCSM:** Mulholland E., Tattini J., Ramea K., Yang C., Ó Gallachóir B. (2018). *The Cost of electrifying private transport – Evidence from an empirical consumer choice model of Ireland and Denmark*, *Transportation Research Part D: Transport and environment* 62, 584-603
- VIII. **Soft-link TIMES-DKMS and DCSM:** Tattini J., Mulholland E., Venturini G., Ahanchian M., Gargiulo M., Balyk O. Karlsson K. (2018). *A long-term strategy to decarbonise the Danish inland passenger transportation sector*, https://doi.org/10.1007/978-3-319-74424-7_9 in Giannakidis G., Karlsson K., Labriet M., Ó Gallachóir B. (eds.), 2018. *Limiting Global Warming to Well Below 2°C: Energy System Modelling and Policy Development*. Springer, *Lecture Notes in Energy*, <https://doi.org/10.1007/978-3-319-74424-7>
- IX. **Nordic EV Outlook 2018:** Cazzola P., Gerner M., Schaffer S., Schuitmaker R., Tattini J. (2018). *Nordic EV Outlook 2018 – Insights from leaders in electric mobility*, IEA, Paris

1.5 Timeline and role of collaborations

Throughout my research work, I have had the luck and the honor to collaborate with some of the leading institutions in the fields of energy system modeling, energy system analysis, transport analysis and transport policy. These collaborations gave me the opportunity to produce original modeling approaches that result to be state-of-the-art concerning the representation of transport behaviour within BU optimization energy system models. The studies published within the scope of my PhD research have been written collaborating with researchers, consultants and analysts working at the Technical University of Denmark, E4SMA S.r.l. (Italy), University College of Cork (Ireland), UC Davis (USA), Chalmers University of Technology (Sweden), International Energy Agency (France) and Danish Energy Agency (Denmark). This section aims at retracing the timeline of my PhD research, highlighting the place where I have carried out the research activities and the institutions I have collaborated with for the different publications. Figure 1 describes such timeline, indicating when the publications have been prepared and which institutions I have collaborated with for their preparation.

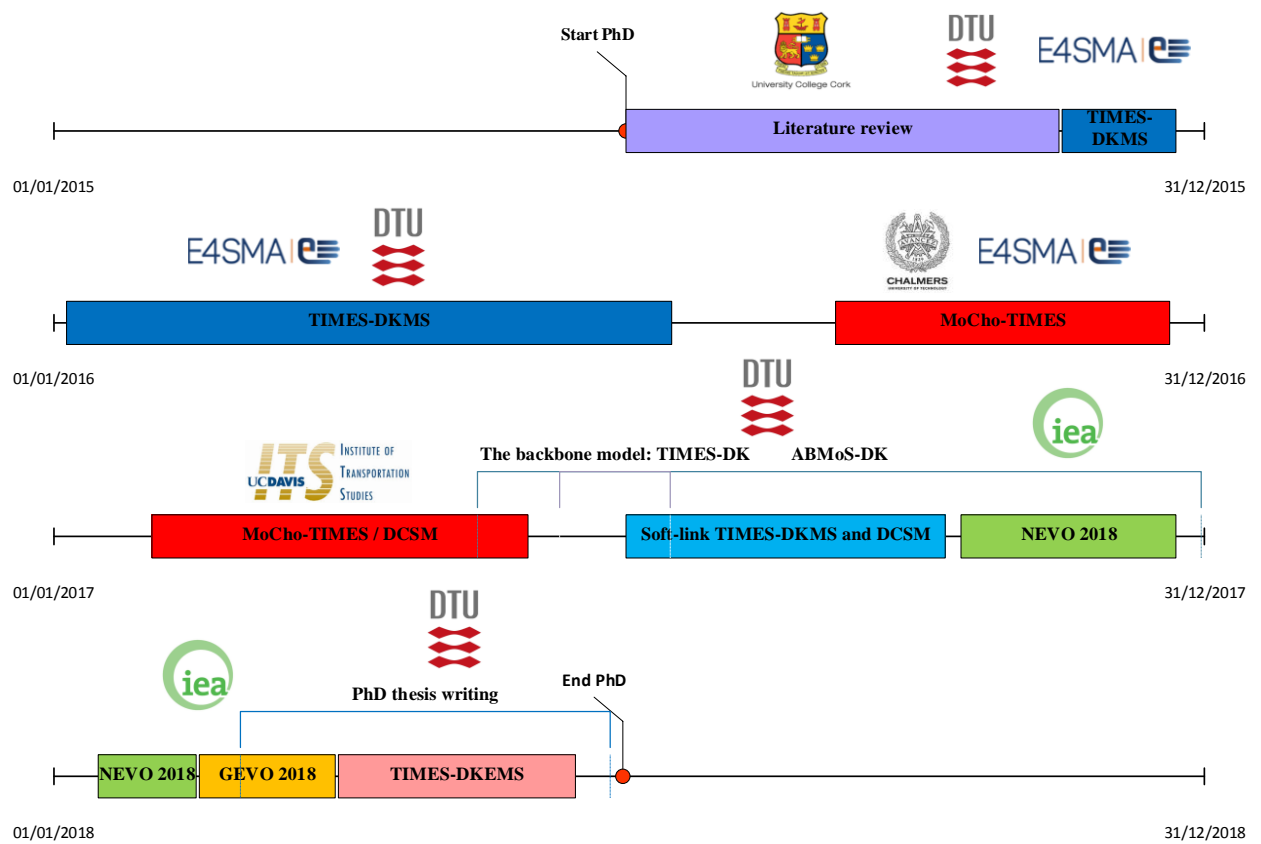


Figure 1: Timeline of collaborations throughout the PhD study period

2 Literature review

RQ 9

In 2012, a review of energy system models identified their weak representation of consumer's choice behaviour [12]. Either the transport market shares were endogenously determined accounting only for the techno-economic characteristics of the different alternatives, or they were exogenous inputs deriving from the assumed consequence of certain energy policies ("what-if analysis") [3, 16 -18]. However, new end-use technologies have to be accepted by people and therefore it is important to include a description of consumers' preferences and their acceptance of different transport technologies in energy models. To tackle this limitation of energy system models, the review suggested the inclusion of five features to improve the representation of behaviour in transport: elastic transportation demand, endogenous modal shift, choice of no (physical) travel, infrastructure capacity, and segmentation of urban and intercity transport. As a response to the weak representation of consumer's choice in E3² models highlighted in [12], there has been a recent trend in attempting to integrate behavioural features in transport within energy system models [11]. Instead of performing "what-if" scenario analyses, the research interest has shifted to the endogenization of modal and vehicle choice in a more behaviourally realistic manner.³ Paper I reviews recent efforts from several research groups worldwide to tackle the criticisms identified in [12]. The critical review in paper I suggests that, among the common approaches for structuring a model⁴, the BU approach is the most promising one to include the representation of human behaviour in transport for climate policy analysis. Firstly, such improved BU models allow for energy system-wide considerations, supporting the understanding of the future reciprocal implications of decisions taken in the transportation sector and in the energy system. Then, a much wider variety of policies involving both technology-related and behavioural variables can be assessed. Moreover, paper I identifies technology choice, modal choice,

² E3 (Energy-economy-environment) models are the equivalent of E4 models. The term E3 is hereby used because it is the acronym adopted in [12].

³ This consists in determining both modal and vehicle shares not only according to cost minimization criteria, but also including other non-economic factors relevant to consumers' choice.

⁴ The approaches for structuring an energy system model are three: top-down, bottom-up and hybrid. Each model approach has its own advantages and disadvantages depending on the scope and purpose of the analysis [11].

driving patterns and new mobility trends as the recurring ways to include behaviour in integrated energy and transport models.

The remaining of this section illustrates the state-of-the-art of the representation of modal and technology choice in integrated energy and transport models before the beginning of this PhD research, which has been the starting point to develop the novel methodologies proposed in Section 3.

2.1.1 Modal choice

Modal choice consists of an individual facing two or more alternative modes of transport among which to choose. Integrating modal choice in E4 models allows to mimic the dynamics of modal shift and to determine endogenously modal splits. According to the classical formulation of discrete choice models [19, 20], individuals choose mode among the available alternatives based on an index of preference called utility, which depends on the characteristics of the alternatives and on the characteristics of the individuals. Traditionally, in discrete choice models the utility of a mode is a linear function of parameters and attributes, plus an error term, which accounts for the fact that the modeller is able to capture only a subset of all the attributes affecting modal choice [20]. These attributes are generally socioeconomic variables, which account for diversity in modal perception across the population, and level-of-service (LoS) variables, defining the characteristics of the alternatives as perceived by the consumers [21]. Discrete choice models calculate the probability that an individual chooses a certain alternative from the set of choices by comparing the utilities of the different alternatives. Rational consumers choose the alternative from which they get the greatest utility. The most popular techniques for simulating modal choice have been logit and probit models, because they are able to account for variation of preferences across the population [22]. Transport models have a long tradition of simulating modal choice. Their structure generally consists in four steps: trip generation, trip distribution, modal choice and route assignment. In the third stage, modal shares are normally determined through multinomial logit model (MNL) or nested logit model (NMNL) accounting for many attributes describing the observed characteristics of the modes and the observed characteristics of the individuals. In the field of E4 models, the representation of modal choice is a more recent area of interest to modellers. Thanks to the inclusion of simulation methods in the model structure, top-down (TD) [23] and hybrid (H) [24, 25] E4 models are able to simulate modal choice through constant elasticities of substitution (CES) and MNL functions, which are well-established methods that have been used for this purpose for long time. On the other hand, BU linear optimization E4 models lag behind TD and H models concerning the ability to simulate modal shift. Traditionally, for BU optimization models the end-use mobility demands are specified exogenously for each mode. Several technologies compete to fulfil the projected mode-specific mobility demands. However, technologies compete within a mode, but not between modes, thus preventing endogenous modal shift [26]. The mathematical formulation of CES and MNL functions cannot be directly adopted in the linear optimization framework. Therefore, for BU optimization E4 models the research on new

approaches for representing modal choice is cutting-edge. Paper I recognizes two main approaches to incorporate modal choice in this class of models. The first consists in linking the BU energy system model with an external transport model that integrates the behavioural features and determines modal shares [27 - 30]. The second mimics modal shift directly within the BU model, by adjusting the model structure to accommodate some transport-specific variables relevant for modal choice [26, 31].

2.1.2 Technology choice

Technology choice in transport consists of an individual facing two or more alternative transport technologies among which to choose.⁵ Incorporating transport technology choice in E4 models allows to endogenously select a transport technology from a set. E4 models traditionally determine the vehicle shares to fulfil the mobility demand only based on techno-economic aspects, disregarding that vehicle preferences are highly heterogeneous and based on many non-economic aspects. Paper I identifies four main methodologies that are generally used to represent vehicle choice in a more behaviourally realistic way: (i) discrete choice models, (ii) CES, (iii) disutility costs and (iv) hurdle rates [11]. A common trait of all these approaches is that they attempt to capture realistic technology choice by including not only monetary parameters, but also some non-monetary parameters that affect consumers' decisions. Due to the non-linear mathematical formulations, the former two methodologies cannot be directly incorporated within linear optimization models to improve the representation of technology choice. On the other hand, disutility costs and hurdle rates could also be adopted in BU linear optimization models [10, 30 and 32]. As for modal choice, the improvement of the representation of technology choice in BU optimization E4 models can either be achieved via a link with an external model that integrates the behavioural features or adjusting the model structure to accommodate non-monetary parameters.

⁵ The concept of technology choice is typically applied to choice of road vehicles.

3 Models and methodologies

Paper I claims that the BU model structure is promising to include a representation of behaviour in transport for climate policy analyses (see Section 2). Moreover, it identifies technology choice and modal choice as key features to incorporate consumer's choice in energy system models. Following these findings, this PhD research has developed several methodologies to improve the representation of behaviour in transport within a specific family of BU optimization E4 models, which is the TIMES (The Integrated MARKAL EFOM System) models. The reason for doing such improvement in this particular class of models lies in the fact that they represent the transport sector as part of the whole energy system. Therefore, in TIMES models it is already possible to analyse the future development of the transport sector considering its interactions, interconnections and potential synergies with the other sectors. And this is particularly important considering that transport is expected to be increasingly integrated with the rest of the energy system in the future. In particular, the backbone model used in this thesis is TIMES-DK, the TIMES model of the Danish energy system. Despite the studies within this PhD research integrate consumers' choice into a TIMES energy system model, the intention is to produce methodologies replicable by any BU optimization energy system model.

In accordance with the findings of paper I, the models developed can be classified in four categories. The first classification is between models that incorporate modal choice and models that improve the representation of vehicle choice. The second classification is between methodologies that accommodate transport-specific variables directly within TIMES-DK, denominated endogenous methodologies, and methodologies implemented in external models to be linked with TIMES-DK, denominated soft-linking methodologies. An overview of the methodologies developed within the scope of this PhD research and their classification is provided in Table 2.

Table 2: Methodologies developed within the PhD research to improve the representation of behaviour in transport, classified according to the behavioural feature addressed and to the soft-linking/endogenous dichotomy

	Soft-linking	Endogenous
Modal choice	ABMoS-DK	TIMES-DKMS, MoCho-TIMES, TIMES-DKEMS
Vehicle Choice	DCSM	

This section first describes TIMES-DK, particularly the representation of the transportation sector, highlighting its main characteristics and limitations concerning the representation of behaviour. Then it describes the novel approaches developed within this PhD project to incorporate modal choice and to improve the realism of vehicle choice in TIMES-DK. Finally, it describes the multi-model approaches created.

3.1 The backbone model: *TIMES-DK*

TIMES-DK is the first energy system model that includes the complete Danish energy system [33, 34]. TIMES-DK is able to describe socioeconomic optimal pathways to a low-carbon Danish energy system optimising simultaneously operations and investments of energy technologies across all energy sectors. TIMES-DK belongs to the TIMES model family, which is described in the next section.

3.1.1 TIMES model generator

The Integrated MARKAL-EFOM System (TIMES) model generator is developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP), a Technology Collaboration Programme of the IEA. TIMES models are BU technology-rich energy system models suited for medium/long-term analysis and planning of national, regional or even city level energy systems. In addition, TIMES is a techno-economic, partial equilibrium model generator assuming full foresight and perfectly competitive markets. TIMES models are linear optimisation problems and the solution is calculated as the minimization of the sum of the total system costs discounted to a reference year, subject to user-defined technological, environmental, resource availability and policy restrictions. The type of inputs used to build the TIMES models are: end-use demand curves, supply curves and techno-economic parameters for each technology represented in the model. The outputs from TIMES models are investments, operation and import/export levels optimal for the energy system as a whole, marginal prices of the energy commodities, emissions and costs. A detailed description of TIMES is provided by [35].

3.1.2 Overview of *TIMES-DK*

TIMES-DK is a multi-regional model geographically aggregated into two regions: Denmark East (DKE) and Denmark West (DKW). It is divided into five sectors: supply, power and heat, industry, residential and transport. TIMES-DK is calibrated for the base year (BY) 2010 and has technological and

economic projections until 2050. This time horizon is sub-divided into shorter periods of various duration, most commonly 1-5 years. In turn, every year comprises 32 non-sequential time slices, representing seasonal (4 seasons), weekly (working/non-working days) and daily variations [33]. Paper II provides a detailed description of the whole TIMES-DK, while the remaining of this section focuses on its representation of the Danish transportation sector.

3.1.3 Transportation sector in TIMES-DK

In TIMES-DK, the transportation sector describes the Danish mobility demands, the end-use transport technologies and the transport fuels (with relative production technologies) [33]. Several fuel chains are available to the transportation sector, some of which make it more integrated with the rest of the energy system (e.g. bio-fuels, electricity and hydrogen). The transportation sector includes passenger and freight transport, further split into aviation, maritime and inland sub-sectors. The inland passenger sector includes ten modes: car, public bus, coach, rail (metro, train, S-train), 2-wheelers (motorcycle and moped) and non-motorised modes (bike and walk). The inland passenger mobility demands are expressed as passenger kilometre (pkm) and are defined exogenously for each mode, from the BY until the end of the modeling horizon. Moreover, inland passenger mobility demands are split by class of distance range: extra short, short, medium and long distances.⁶ Figure 2 describes the structure of the inland passenger transportation sector of TIMES-DK.

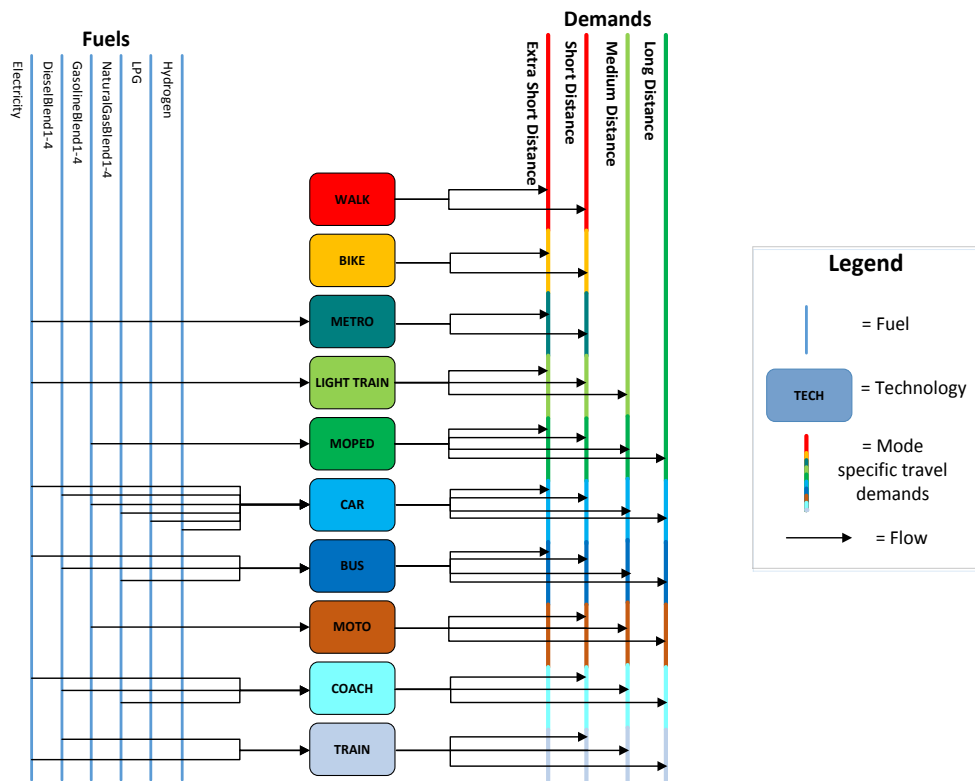


Figure 2: Structure of the inland passenger transportation sector in TIMES-DK

⁶ Extra short (XS): ≤ 5 km; Short (S): 5-25 km; Medium (M): 25-50 km; Long (L): > 50 km.

The technology database for the transportation sector of TIMES-DK includes existing technologies and technologies that are available for future investments. These technologies compete to meet the exogenously projected mobility demands. It is worth noticing that technologies can compete within a mode, but not among modes (i.e. modal shift is not possible). In addition, competition between transport technologies is based on technology and fuel costs, while complying with the constraints: TIMES seeks to meet the modal mobility demands with the portfolio of technologies characterized by the lowest levelized costs⁷, while complying with the constraints. Another shortcoming inherent to the optimisation approach is that TIMES-DK assumes the role of a central energy planner, who makes decisions on behalf of the average consumer with full information, perfect rationality and aiming at maximising the economic utility of the system. This does not allow to capture all the aspects related to consumer behaviour, which play a fundamental role in decision-making processes [11, 19, 20 and 22].

3.2 *Representation of modal choice*

Departing from the traditional representation of the passenger transportation sector described in Section 3.1.3 for the case of TIMES-DK, this section briefly describes four approaches developed within the PhD study to incorporate modal choice within BU optimization E4 models.

3.2.1 TIMES-DKMS

TIMES-DKMS (TIMES-DK with modal shift) is a version of TIMES-DK that determines modal shares endogenously within the inland passenger transportation sector. This process forgoes changing the core modeling paradigm of TIMES, only altering the conventional model structure. The mode- and length-specific mobility demands are merged into length-only specific transport service demands, thus introducing competition among modes and enabling modal shift. Modal competition is determined considering both the levelised cost of the modes and new parameters in the TIMES framework: speed and infrastructure requirements. Modal speeds are complemented by a constraint on the travel time budget (TTB), historically observed for the Danish transportation sector [36]. The TTB ensures the competitiveness of faster yet more expensive modes in a cost-optimisation modeling framework [26]. Infrastructure accounts for the cost of adapting the existing transport networks capacity to demand increases and possible significant levels of modal shift. Infrastructure requirements regulate modal shift, as this may end up in infrastructure saturation, subsequently requiring additional infrastructure capacity, which implies a cost [37]. Figure 3 provides a schematic description of the structure of TIMES-DKMS.

⁷ In TIMES models, normally the costs accounted are related to the supply of the energy resources and to the technology capacity expansion and operation. They normally include actualized investment costs, fixed and variable operation and maintenance (O&M) costs, fuel costs and delivery costs.

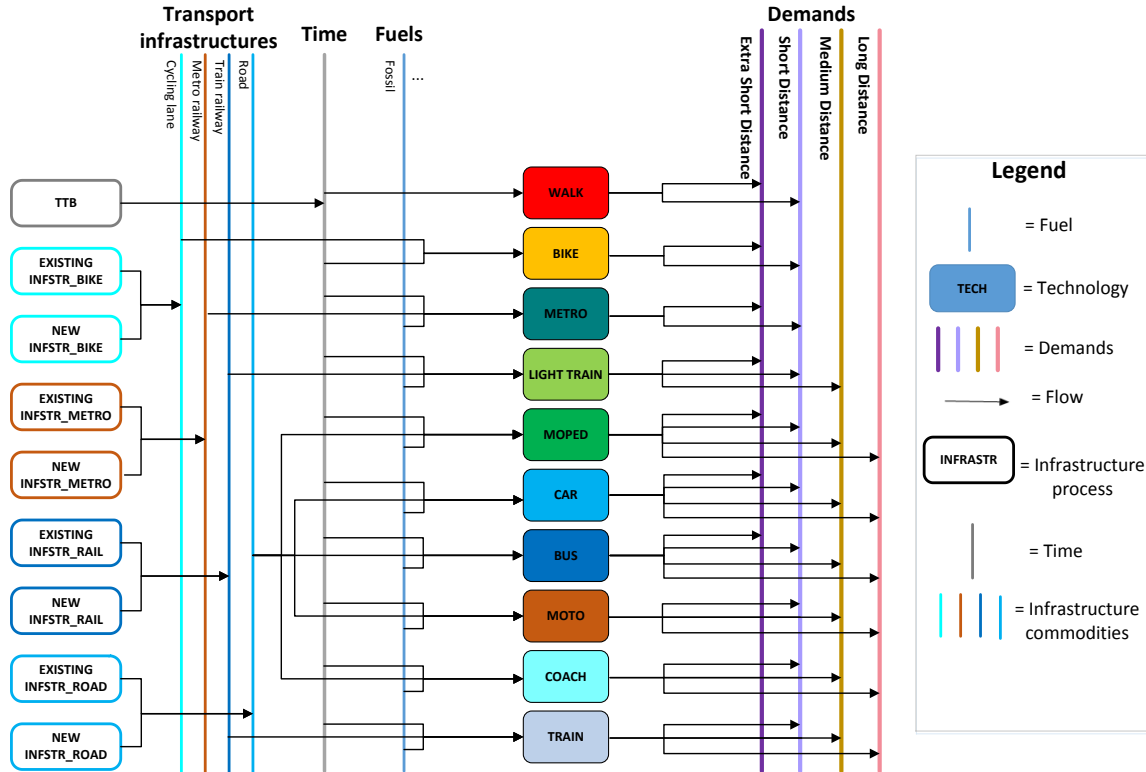


Figure 3: Structure of the inland passenger transportation sector in TIMES-DKMS

Being the structure of the model re-organized as in Figure 3, some additional constraints on the maximal and minimal modal shift and on the rate of shift based on the observations of a travel survey [36] are included in TIMES-DKMS to ensure realistic modal shift. Paper III provides a detailed description of the model. TIMES-DKMS outputs the least-cost decarbonisation pathway that meets all the constraints included in the model as a co-optimization of the modal shares and vehicle shares. The modal shift option provides TIMES-DKMS additional flexibility, since it can meet the environmental targets by increasing the market shares of some modes at the expense of other ones. However, the soft variables influencing modal choice [21] have been neglected, and modal shift is endogenously determined via a suitably constrained socioeconomic optimization that assumes a central decision-maker.

3.2.2 MoCho-TIMES

MoCho-TIMES (Modal Choice in TIMES) incorporates modal choice in the standalone transportation sector of TIMES-DK [21]. This approach determines endogenously the modal shares by incorporating several attributes that affect modal choice. These attributes can be aggregated in two classes: socioeconomic and demographic attributes (region and type of residential location, and income level), and LoS attributes (in-vehicle time, congestion time, waiting time, walking time, etc). The former class of variables influences consumers' perceptions and preferences, the latter defines the characteristics of the modes. Consumer heterogeneity is introduced in the model framework to capture the diversity in modal perceptions across different consumer groups. The total travel demand is split into segments

corresponding to groups of transport users with similar socioeconomic and demographic characteristics. The heterogeneous modal perceptions are quantified via monetization of intangible costs. The intangible costs consist in a change in the expression of the modal costs, to introduce the non-monetary costs perceived by transport users and to differentiate the modal perception across the diverse consumer groups defined in the model. In fact, the same mode has associated to each consumer group a specific intangible cost. This is due to the expression of the intangible costs, which is the product of the LoS (affected by the type of residential location) and the value-of-time (VoT)⁸ (related to the income level). In addition to consumer heterogeneity and intangible costs, MoCho-TIMES incorporates also other features that influence individuals' modal choice (monetary budget, requirement of transport infrastructures, TTB, travel patterns, maximum shift potential and maximum rate of shift). Paper IV provides a detailed description of the model. A simplified schematic overview of the structure of MoCho-TIMES is provided in Figure 4.

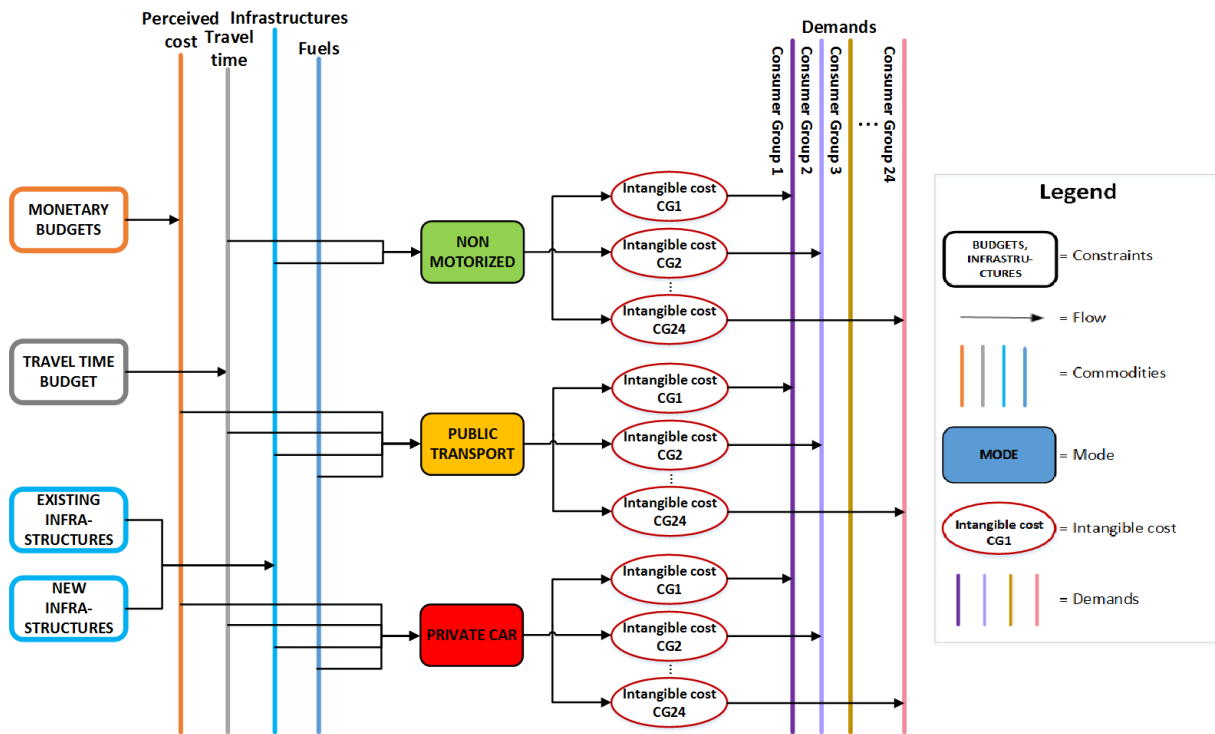


Figure 4: Structure of MoCho-TIMES

In MoCho-TIMES, each group of transport users chooses its own optimal set of modes and technologies, thus leading to a variety of modes each year. A transport simulation model consistent with the geographical scope of the analysis has worked as support model, providing the mathematical expressions and data to develop MoCho-TIMES. This model is Landstrafikmodellen, the Danish National Transport Model (LTM) [39, 40].

⁸ The VoT is the marginal substitution cost between travel time and travel cost, and it states how much a consumer is willing to pay in order to reduce the travel time of one unit [38].

3.2.3 TIMES-DKEMS

TIMES-DKEMS (TIMES-DK with elastic modal shift) is a standalone version of the transportation sector of TIMES-DK that utilizes elastic demand functions to determine modal shift endogenously [41]. TIMES-DKEMS incorporates the volume-preserving variant of the elastic demand functions that have been recently released in a new version of the TIMES code, called TIMES-Micro [42]. In TIMES-DKEMS, each distance range class of the travel demands represents an elastic aggregate, for which an elasticity of substitution σ_k (with $k=XS, S, M$ and L distance range) is defined. The elasticity of substitution is the same for all the demands within the aggregate, but can be different across aggregates and along the years of the time horizon. The structure of TIMES-DKEMS is presented in Figure 5.

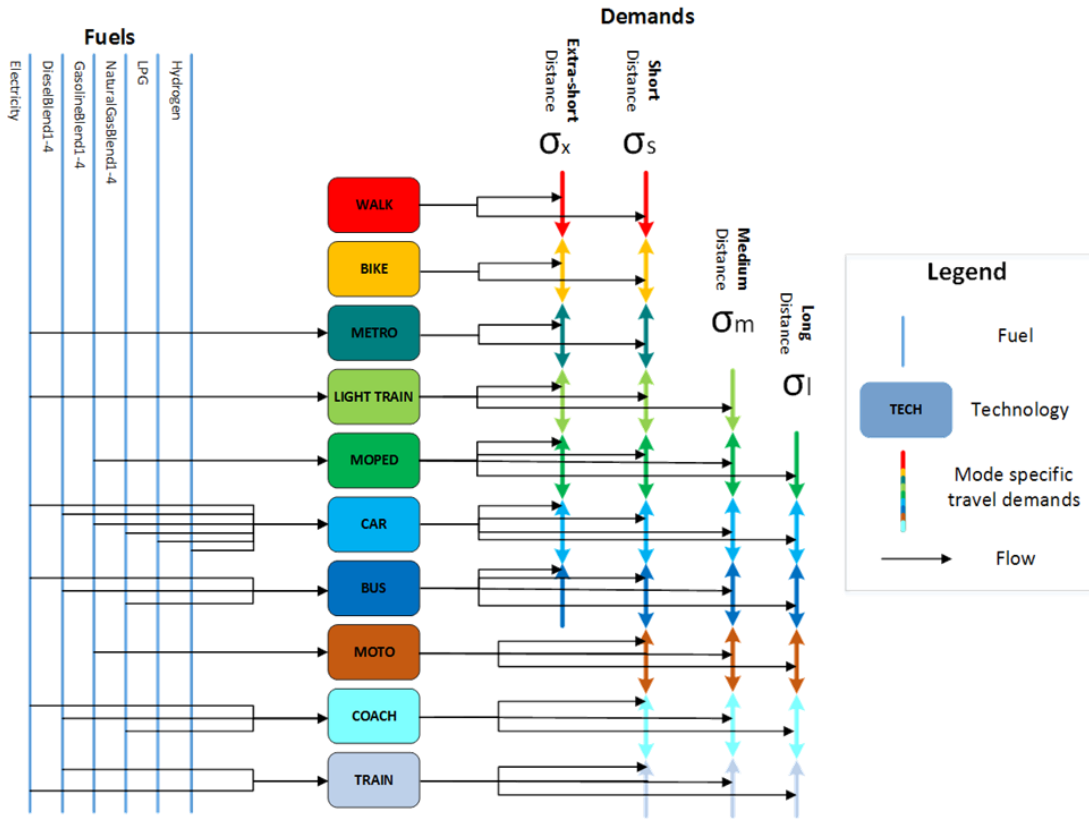


Figure 5: Structure of TIMES-DKEMS

In TIMES-DKEMS, the demands within an aggregate adjust their levels in reaction to changes of their shadow prices with respect to a reference case, while the total demand within the aggregate is conserved, due to adoption of the volume-preserving variant of the elasticities of substitution. In paper V, elastic modal shift is allowed from 2020 onwards. In order to incorporate elastic modal shift within the TIMES model paradigm, the formulation of the elasticities of substitution has been linearized [42]. Besides elastic demand functions, modal shift in TIMES-DKEMS is regulated through a set of constraints that limit the maximum and minimum modal shift in each distance-range and through travel patterns defining the fulfilment of the travel demand in the various distance ranges.

3.2.4 ABMoS-DK

ABMoS-DK (Agent Based Modal Shift model of Denmark) is an agent-based (AB) model that accounts for travelers' behaviour to simulate modal choice for the Danish inland passenger transportation sector [43]. With respect to the classification described in Section 3, ABMoS-DK falls in the category of soft-linking methodologies, as it determines modal shares outside of the TIMES model. Inherently to the BU approach that characterises AB models, the characteristics of consumers are described with high level of detail within ABMoS-DK. The thorough representation of consumers' heterogeneity enables to differentiate the preferences affecting modal choice across consumer groups. Transport users with homogeneous characteristics (similar type of residential area, income level, age, car ownership, bike ownership and driver's license) are regarded as an agent. Agents are assumed independent, which means that they do not interact and that the transport mode chosen by a certain agent does not depend on the choice made by other agents. For each trip, agents choose the mode of transport based on a series of rational decision rules described in a mode choice algorithm. This algorithm considers the socioeconomic and demographic characteristics of the agents and the characteristics of the trip (type of origin and destination, trip length, trip purpose, departure time and LoS measures) and then compares the utility of the alternative modes available, choosing the one with the highest utility. The utility of the modes is calculated as a combination of tangible costs (ticket price, fuel price, vehicle taxes, etc.) and intangible costs (from LoS and VoT measures). The intangible costs assume different values across diverse agents, due to the different perception of the LoS of the modes across the heterogeneous agents. ABMoS-DK is calibrated by adjusting the decision rules in the mode choice algorithm to reproduce the historical modal shares between 2010 and 2015. Further details about this model are provided in Paper VI.

3.3 *Enhancements to vehicle choice representation*

The traditional representation of vehicle choice in BU optimization E4 models is purely techno-economic: an average decision maker chooses the cost-optimal vehicles considering the technical and economical characteristics of the options available, disregarding any behavioural feature [44, 45]. This PhD research has contributed to improving such representation by collaborating to the development of the Danish Car Stock Model (DCSM), a simulation model of the car sector intended to be soft-linked with TIMES-DK. The DCSM is a simulation model composed of two core components: a socioeconomic consumer choice model and a techno-economic CarSTOCK model. The remaining of this section shortly describes these two components, while paper VII describe the model in detail.

3.3.1 Consumer choice model

The consumer choice model component of the DCSM determines the market shares of different types of private cars in the Danish market via the simulation algorithm employed in the CIMS H E4 model [46].

This algorithm uses the tangible costs (investment cost, maintenance costs, fuel cost and vehicle-related taxes) and monetized intangible costs (model availability, risk related disutility, range anxiety, and refuelling infrastructure) faced by the consumers to calculate the market shares for the different car technologies available in a specific year in Denmark [47]. The DCSM integrates heterogeneity of private car preferences through splitting transport users into 18 segments, divided geographically, by driving profile and by adoption propensity. Five technologies split into three categories are represented in the model: gasoline internal combustion engine (ICE), diesel ICE, natural gas (NG) ICE, battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) disaggregated into the classes small, medium, and large for ICEs (based off engine size) and into short, medium, and long range for BEVs (<125km, 125-175km, >175km respectively). The consumer choice model generates the market shares of the private car stock and outputs this result to the CarSTOCK model, which determines stock projections, energy consumption and CO₂ emissions, as shown in Figure 6.

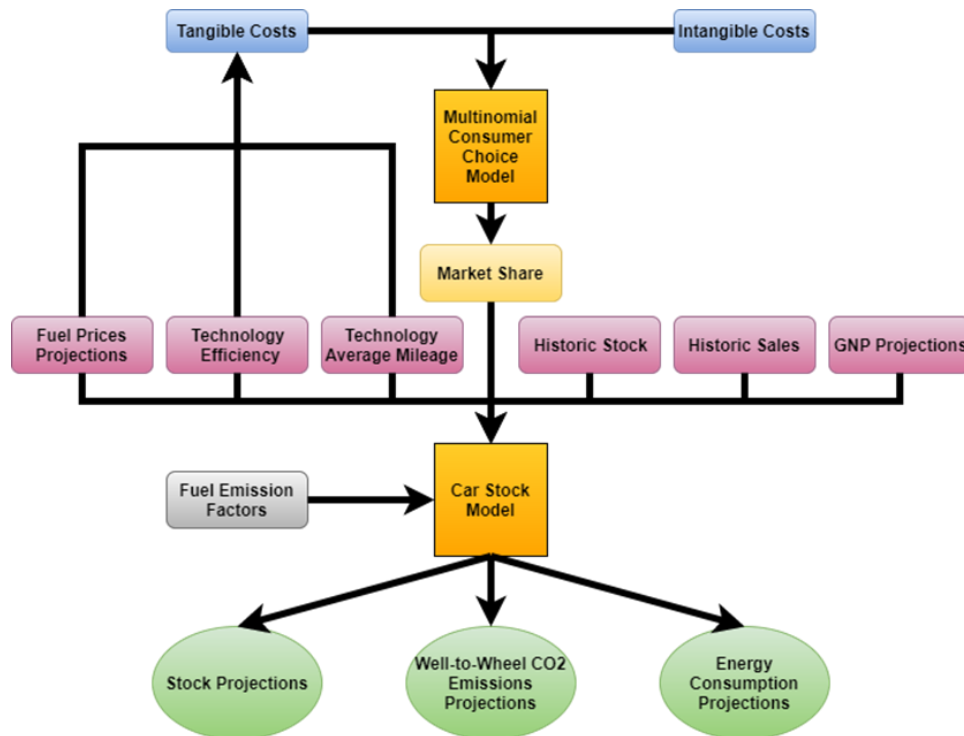


Figure 6: Integration of consumer choice model and CarStock model with DCSM

3.3.2 CarSTOCK model

CarSTOCK is a BU model that combines cars' market shares calculated in the DCSM consumer choice model and retirement profiles to analyse the long-term evolution of the car stock, fuel consumption and CO₂ emissions in Denmark [47]. The CarSTOCK model has a detailed disaggregation of private car technologies into technology type (in line with those in the consumer choice model) and 30 vintage categories to represent the evolution of the car fleet. The CarSTOCK model draws upon detailed Danish statistics relating to the composition of private car sales, annual mileage, fuel economy, and vehicle life-time with a disaggregation of vintage, fuel type and engine size (driving range for BEVs).

3.4 Multi-model approaches

Integrating models has become an increasingly common approach in the field of energy system modeling [45, 48 and 49]. Combining different modeling approaches can take advantage of the strengths of individual methodologies and can add value and insight to individual approaches. Within the scope of this PhD research, two multi-model approaches have been developed: TIMES-DKMS has been soft-linked to the DCSM and TIMES-DK has been soft-linked to ABMoS-DK (Figure 7).

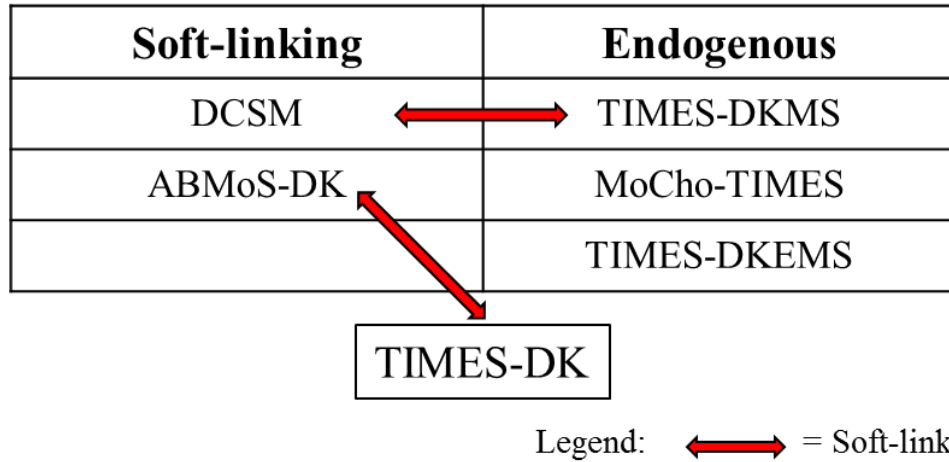


Figure 7: Soft-link of the models developed within the PhD project

3.4.1 Soft-link of TIMES-DKMS and DCSM

This modeling framework integrates modal shift and behaviourally realistic vehicle choice via soft-linking TIMES-DKMS and the DCSM to inform the policy making process for the transportation sector in Denmark while accounting for the interconnections and interactions with the whole energy system. First, TIMES-DKMS determines the optimal technology investments to meet the endogenous future end-use demands at the least overall systems cost. Then, the DCSM checks the technical feasibility of the technology portfolio deployment pattern within the private car sector obtained with TIMES-DKMS [50]. If the solution is not feasible, capacity constraints bounding the stock of specific car technologies are added in TIMES-DKMS to comply with the realistic car shares projections calculated by the CarSTOCK model. A new solution is obtained with TIMES-DKMS, which is again verified in the DCSM. Data exchange between the two models is iterated until there is convergence between the results (Figure 8).

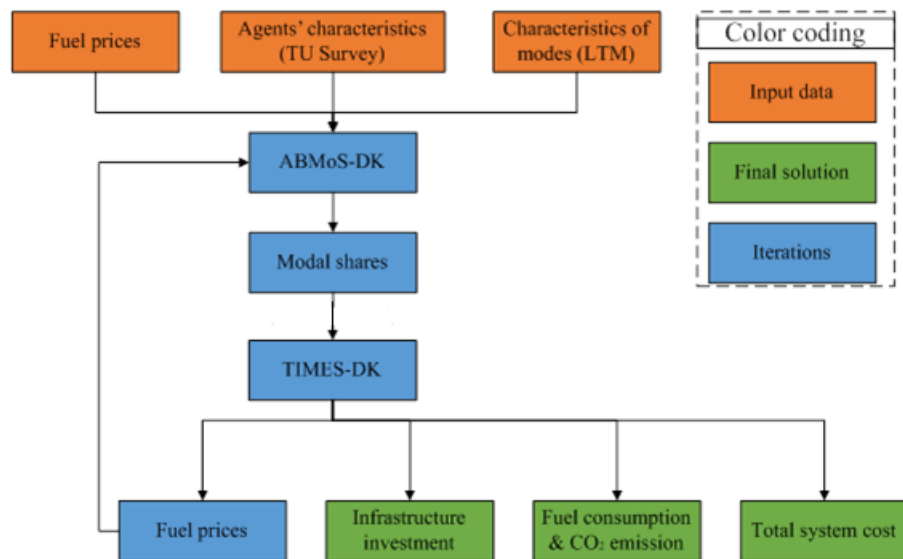


Figure 9: Model integration between ABMoS-DK and TIMES-DK

This modeling framework is able to explore the effect of policy measures on modal shares and their influence on the whole energy system. The behaviourally realistic modal choice incorporated in ABMoS-DK is coupled with the holistic view on the entire energy system of TIMES-DK.

4 Analyses and main results

This section summarizes the main results of the analyses carried out during this PhD research. It is important to note that the results hereby presented are not comprehensive of all the analyses performed within the COMETS project [52].⁹ The work package (WP) that this PhD has mostly contributed to was strongly focused on modeling, aiming at developing a state-of-the-art representation of the transportation sector within BU optimization E4 models that incorporates realistic consumers' choice [53]. In parallel, another WP was focused on adopting the models that I have developed to analyse transport scenarios leading to 100% renewable energy system in Denmark and to analyse policies promoting the sustainable pathways identified [53]. The results presented in the remaining of this section are part of those produced by my WP. They are structured in a manner to answer to the RQs listed in Section 1.2. However, the models and methodologies described in Section 3 have been used by the other WP for several other analyses, e.g. how changes in end-users' behavior in transport and energy affect the rest of the energy system and, on the other side, how modal shares and fuel consumption in the transportation sector are influenced by decisions in the power and heat and other end-use sectors [54, 55].

4.1 *Potential contribution of modal shift to cut GHG emissions*

RQ 1

The contribution of modal shift to the decarbonisation of the Danish energy system has been analyzed in paper III by comparing the results of TIMES-DK (Section 3.1) with those of TIMES-DKMS (Section 3.2.1). Modal shift is found to have a potential positive contribution to the decarbonisation of the Danish energy system. The analyses prove that modal shift enables reaching carbon-neutral transportation (and energy) system in Denmark in 2050 at faster pace, as visible in Figure 10. Moreover, the optimal

⁹ COMETS (Co-Management of Energy and Transport System) is the main research project of this thesis. COMETS aims at finding “opportunities to maintain mobility trends and energy supply while at the same time allowing for a smooth transition to more renewable energy in the transport sector. COMETS does this by delivering a new analytical framework and model system going beyond state of the art in energy system modeling by combining infrastructure planning, transport behavior, and energy system integration” [52].

decarbonisation pathway identified considering modal shift as an option leads to about 1.9% lower cumulative CO₂ emissions from the whole energy system (5.2% lower CO₂ emissions from the transportation sector) and 1.5% lower system costs with respect to the case in which modal shift is neglected [37].

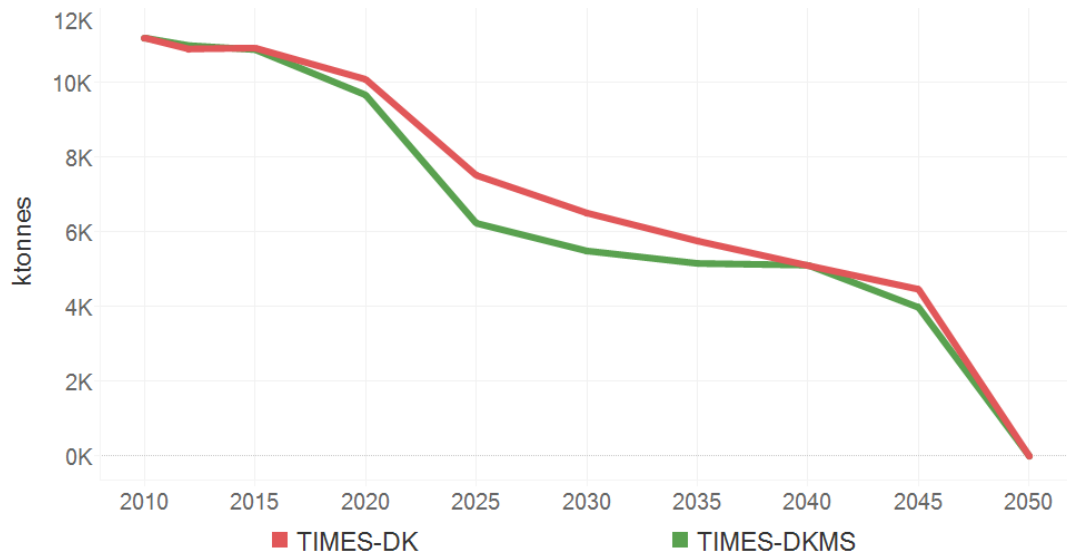
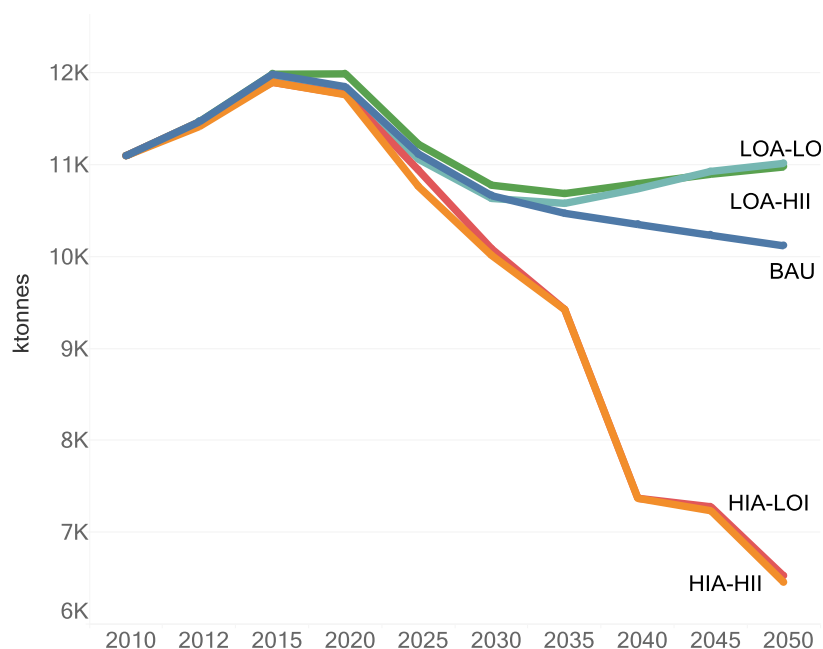


Figure 10: CO₂ emissions reduction from the Danish inland transportation sector in the CO₂ free scenario of TIMES-DK and TIMES-DKMS

The analyses carried out in Paper IV conclude that if the authorities would actively encourage modal shift from cars towards more efficient modes of transport, CO₂ emissions from the Danish inland transportation sector in 2050 could be cut of approximately 35% with respect to 2010 levels [21]. On the other hand, a low commitment of the authorities in the promotion of sustainable transport may imply even higher CO₂ emissions than in the business as usual (BaU) scenario (Figure 11).



4.2 Optimal level of shift away from car

In paper III, the highest shift away from cars is achieved through a less strict TTB. In this scenario, around 14% of the total car demand in 2050 is replaced, mainly by buses [37]. Nonetheless, cars continue having the greatest modal share by far in all scenarios analysed in Paper III. Paper IV finds that the highest shift away from car transport is achieved when the authorities and transport users are aligned to achieve a more sustainable transportation system. Also this study concludes that the optimal level of shift away from cars in Denmark in 2050 is approximately 13% of the total car demand in 2050. The differentiation of modal adoption across consumer groups enabled by MoCho-TIMES reveals that transport users who live in rural areas have fewer options available to shift away from car, leading to an increase in the use of car transport over the modeling horizon. On the other hand, urban and suburban areas are served by a wider variety of modes, allowing to limit the use of car transport in the long run (Figure 12). The analyses in paper IV also find out that lower income classes are more willing to shift away from car transport, while wealthier people are more reluctant to reduce the use of cars.

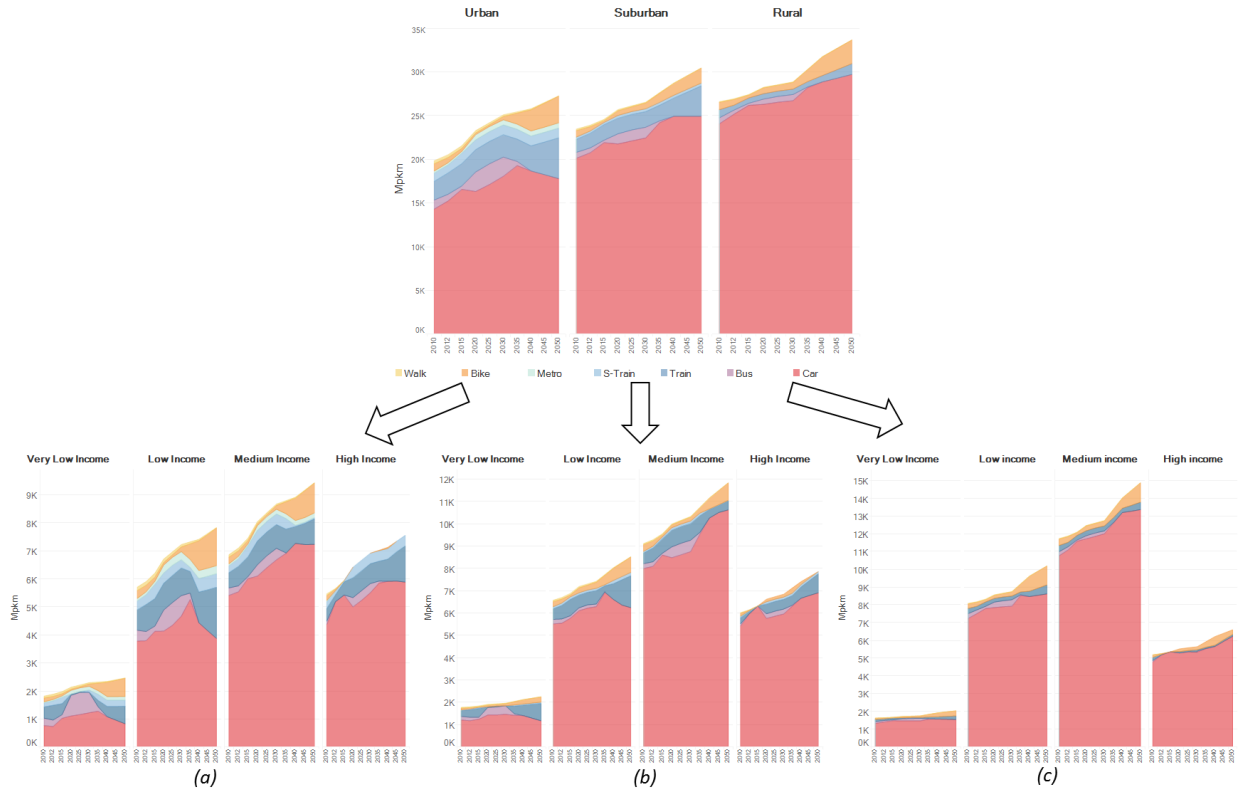


Figure 12: Modal shares in MoCho-TIMES for the three types of residential location, disaggregated at income group level (aggregated for DKE and DKW). (a) urban, (b) suburban, (c) rural

Similar conclusions concerning shift potentials for the consumers living in different types of residential locations and with different income levels are also obtained in paper VI. Nonetheless, under a very ambitious policy package that implies expanding the infrastructures of public transport, improving the

LoS of public transport, incentivising generously public transport and increasing taxes on ownership and operation of cars, Denmark has the potential to almost half the use of cars compared to the BaU scenario in 2050 [43].

RQ 4

4.3 Future composition of the car stock

The evolution of the car stock has been analysed in three different papers: paper III, paper VII and paper VIII. Despite different modeling assumptions and several updates of the model inputs have led to some differences among the composition of the car stock across the papers, a common outlook can be identified. This section first presents the latest and most updated results and then explains the major differences across studies. Given that the behavioral representation of vehicle choice intrinsic in the DCSM offers a more comprehensive view on the characteristics of cars accounted by consumers, its results are more reliable than those obtained with a least-cost optimization techno-economic model. Both paper VII and paper VIII find out that without policy measures the car stock in Denmark is likely to remain largely based on gasoline and diesel ICEs until mid-century: in the BaU scenario, alternative fuelled vehicles (AFV) make up for only 2.5% of the total car stock in 2050 [50]. Paper VII finds out that the high cost associated with the Danish vehicle registration tax (VRT) hinders the penetration of AFVs even if the number of AFV models available for sale increases significantly (thus reducing the model availability risk related disutility). Both paper VII and VIII find out that policy measures reducing AFVs' purchase price or alternatively bans on the sale and import of ICE cars are required to enable the penetration of AFVs in the Danish car stock. Figure 13 shows the evolution of the car stock from paper VIII.

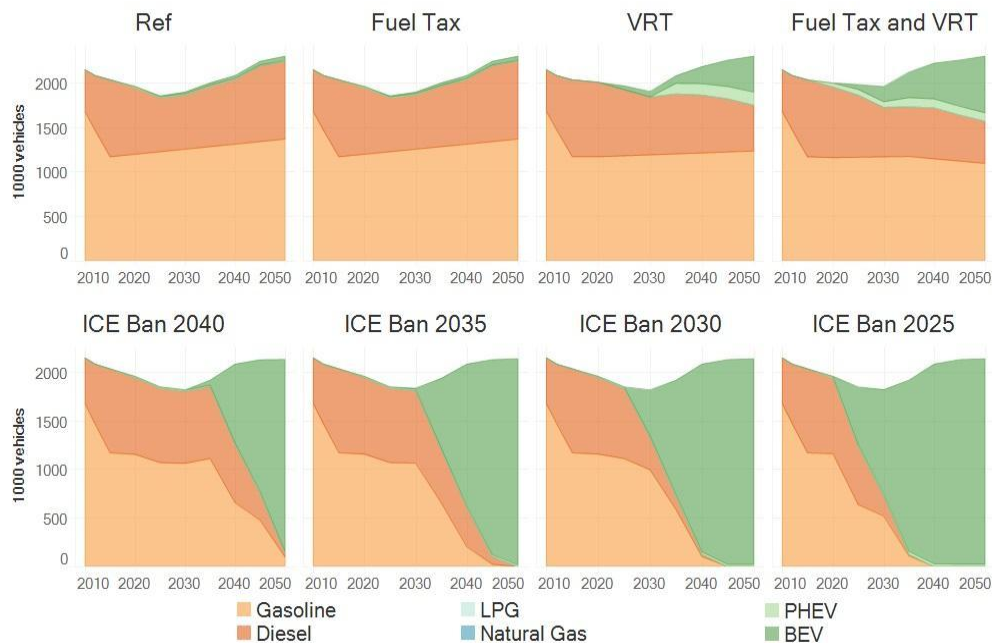


Figure 13: Evolution of the car stock and car technologies in time across scenarios in TIMES-DKMS analysed in paper VIII

The derogation of the VRT on EVs enables a significant electrification of the car stock by 2050, while the combined effect of fuel tax and VRT derogation accelerates the process of electrification of the car stock. Finally, setting a ban on the sale and import of vehicles run solely by an ICE promotes the total electrification of the car stock.¹⁰ Among electric vehicles (EV), PHEV cars only reach a significant share of the total stock in the VRT scenario, which demonstrates that the major barrier to the wide deployment of this technology is its high investment cost [50]. Also Paper VII finds that PHEV cars make appearance only in the scenario that derogates all taxes on this type of vehicle, which manages to close the price gap with other ICE and AFV cars.

The largest difference between the results of paper VII and VIII, and the results of paper III lies in the adoption of gas ICE cars, which in the latter study are identified as cost-optimal transition technologies and as cost-optimal complementary technologies to electric cars in the long-term. Such difference is mainly due to two reasons: on one hand, the investment cost reduction assumed in paper III for gas ICE cars [56] was very optimistic and thus has been revised in the later versions of the model with new assumptions [57]. On the other hand, the inclusion of intangible costs reveals that, due to the low availability of gas ICE car models, the real consumers' perception of gas ICE cars is worse than what would have been suggested by a less comprehensive analysis [50].

Box 1 • Integrating realistic technology's retirement profiles in TIMES models

Another limitation of TIMES models (not strictly related to consumers' choice in transport) has been improved with the contribution of this PhD research. Policy analyses conducted with national TIMES models identified that the representation of retirement profile in the car sector is overly optimistic [50, 58]. In traditional TIMES models, the capacity of future installed technologies is constant until the end of the lifetime. However, analyses on cars' retirement profiles find out that the real-life retirement profiles are far from constant [47]. They are characterised by a low decay in the first years after purchase and by a long tail in the distribution, meaning that few cars remain in the car stock for long time. Thanks to the request stemming from this PhD research, the latest version of the TIMES code (v4.2) is equipped with a novel capacity shape attribute that enables to improve the representation of new technologies' retirement profile [59]. A study utilizing the capacity shape attribute within TIMES-DKMS soft-linked to the DCSM has been carried out, aiming at reaching a more realistic representation of the future composition of the car stock [60]. The study incorporates the real-life cars' retirement profiles [47] and finds out that an early ban on sales and import of ICE cars is not sufficient to decarbonise the Danish inland transportation sector by 2050 (Figure 14). Scrapping incentives are needed to replace old ICE cars with low- and zero-emission vehicles, thus enabling the fulfilment of

¹⁰ Actually this result is unprecise, due to the lack of realism in the representation of new technologies' retirement profile in TIMES models. A solution to this limitation has been proposed and tested and the results are provided in Box 1.

the Danish environmental targets in 2050.

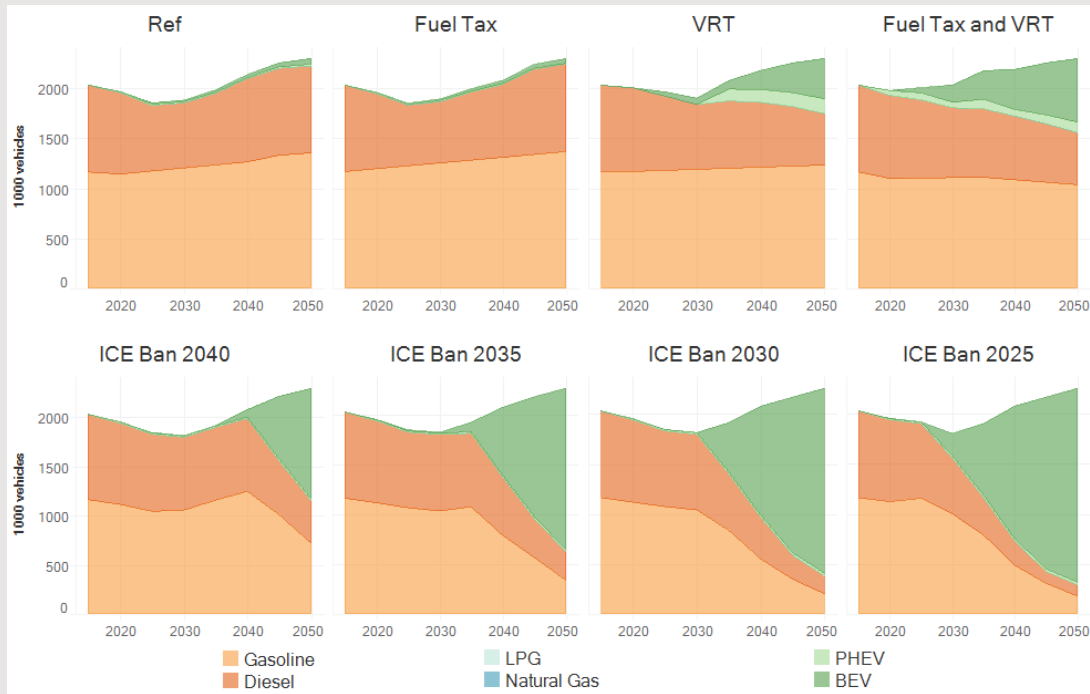


Figure 14: Car stock evolution between 2015 and 2050 according to TIMES-DKMS equipped with the novel capacity shape attribute

4.4 Compliance of GHG emissions reduction pathways with a <2°C future

RQ 5

Paper VIII assesses the compliance of the Danish decarbonisation target and the potential contribution of transport policies to a well-below two-degree future. The cumulative emissions from the Danish energy system have been compared to a range of national carbon budgets, calculated to adhere to various levels of global temperature rise (1.5°C - 4°C) at different levels of confidence (33% - 66%) [50]. The carbon budgets for Denmark have been calculated from those reported in the IPCC 5th Assessment Report [61], based on population (“equity”) and emissions (“inertia”) criteria, following the approach proposed in [62]. The results of paper VIII indicate that a ban on the sale of ICE cars enforced in 2025 would enable the largest cut in cumulative GHG emissions of all the policies considered. Granted a fossil-free by 2050 target is achieved in all sectors excluding inland passenger transport, the policy scenarios analysed indicate that cumulative GHG emissions from the entire Danish energy system in 2050 are in line with a national contribution to an increase in global temperatures of 1.75-2°C (Figure 15).¹¹

¹¹ Excluding the possibility of negative emissions in the second half of the century.

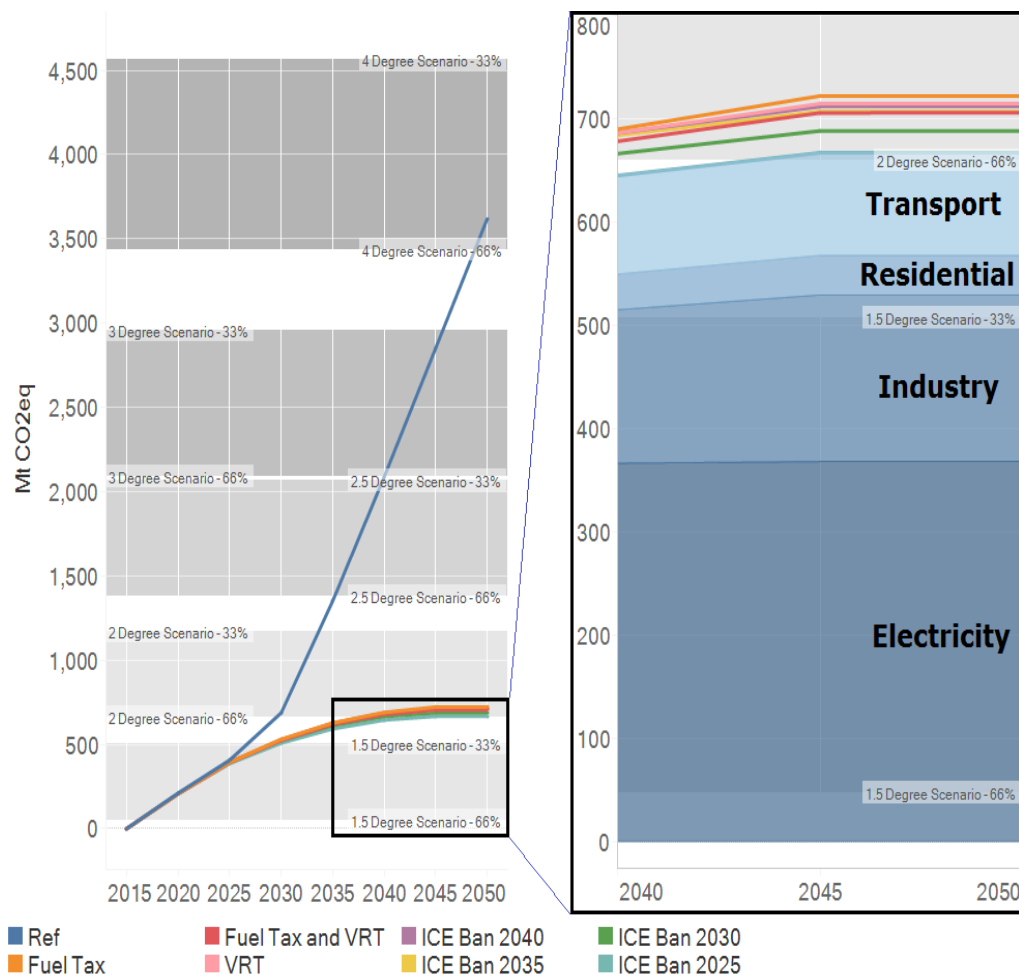


Figure 15: Cumulative GHG emissions from the entire Danish energy system from the policies analysed in Paper VIII

5 Policy implications and recommendations

The analyses carried out within this PhD research are intended to inform Danish policy makers dealing with energy and transport planning on the beneficial contribution of modal shift and of the electrification of the car stock to the compliance with the Danish environmental targets [63] and with the Paris Agreement [64]. This section first suggests some policy measures that should be put in practice in order to accomplish modal shift towards more energy efficient modes of transport. Then, it recommends the policy levers that the authorities should adopt to promote the uptake of electric cars.

5.1 *Policies encouraging modal shift away from private cars*

RQ 6

The analyses performed within the scope of this PhD project prove that modal shift potentially has a significantly positive contribution to the decarbonisation of the Danish transport and energy system [21, 37]. Despite the analyses suggest that a considerable shift away from car transport seems difficult to realize, policy makers should put in practice measures to promote it. Following such findings, this section suggests which policy levers should be implemented to encourage a shift from private cars to less carbon-intensive modes, such as non-motorized modes and public transport. Public transport and non-motorized modes compete with cars in different trip distances: metro, bicycle and walk are valid substitutions to car transport in short distance, while train, S-train and bus in long distance. The findings of paper IV highlight that the authorities should lead the transition towards a sustainable transportation system. Without authority's support, the efforts of individuals alone to reduce the carbon intensity of the transportation sector tend to nullify. Authorities should build additional public transport infrastructure (e.g. for train, S-train and metro) as a precondition to improve the accessibility and the LoS of public transport. Creating lanes restricted to public buses could increase their speed at the expense of cars, thus improving the attractiveness of buses compared to cars. Alternatives to cars for traveling need to be provided more broadly, especially in rural areas, where there is a higher reliance on private cars and a lower modal shift potential. In addition, the taxation and incentive schemes should be designed in such a way as to improve

the perception of public transport and non-motorized modes over private cars. Finally, policy makers should induce a behavioural change so that transport users are willing to accept spending more time traveling. This is especially important for wealthier transport users, who are less receptive to the policies analysed in the various studies due to their higher VoT [21, 43].

5.2 Policies promoting EV car uptake

RQ 7

RQ 8

Besides shifting away from car transport towards more efficient modes of transport, the Danish strategy to comply with the national environmental targets and with the Paris Agreement should also aim at decarbonising the car sector. This is of primary importance, given that even in the most ambitious scenarios analysed within this PhD research [43] cars still account for approximately 43% of the passenger inland mobility demand in 2050.¹² Both paper VII and paper VIII suggest that the decarbonisation of the Danish car sector should be achieved through the deployment of electric cars (combined with the decarbonisation of the power grid). The next two subsections report the Nordic experience and the findings of the modeling analyses carried out within this PhD research concerning the policy framework needed to ensure a large-scale and sustainable transition to electric mobility.

5.2.1 Nordic experience on electric car uptake

The Nordic region – comprising Denmark, Finland, Iceland, Norway and Sweden - is at the forefront of the global electric mobility uptake. Taken together, Nordic countries have one of the highest ratios of electric cars per capita in the world. In 2016, the Nordic region was the world's third-largest electric car market by sales volume after China and the United States [65].¹³ Recognising that the Nordic region is a world leader in electric cars in terms of share of sales, publication IX identifies the key factors that have been contributing to such success and the lessons learned that may guide other countries that are undertaking electric mobility strategies. Generally, at an early stage of electric car market deployment, policy support is indispensable to encourage the uptake: it makes EVs more appealing for consumers, it reduces risks for investors and it encourages manufacturers to scale up production [5]. The Nordic region is no exception to this paradigm and policy support has been the main driver of electric car adoption. Measures that reduce the upfront purchase price of electric cars have been the main driver influencing the decision to purchase an electric car in Norway, with VAT and VRT exemption as the most important factors (Figure 16) [65, 66]. Other important measures are reduced circulation taxes and local policies, including waivers or partial exemptions on road use charges, free parking or access to bus lanes.

¹² Other less ambitious scenarios evaluated in paper III, paper IV and paper V found out that car's share of total passenger inland transport demand in 2050 will range between 66% and 86%.

¹³ In the Nordic countries, the stock of electric cars reached almost 250 000 units by the end of 2017 and accounted for roughly 8% of the global stock of electric cars in 2016. Over 70% of the region's stock is located in Norway. The sales of new electric cars in the Nordic region reached around 90 000 in 2017. The market shares of electric cars of the Nordic countries are amongst the highest globally, and the average for the region is 10.6% [65].

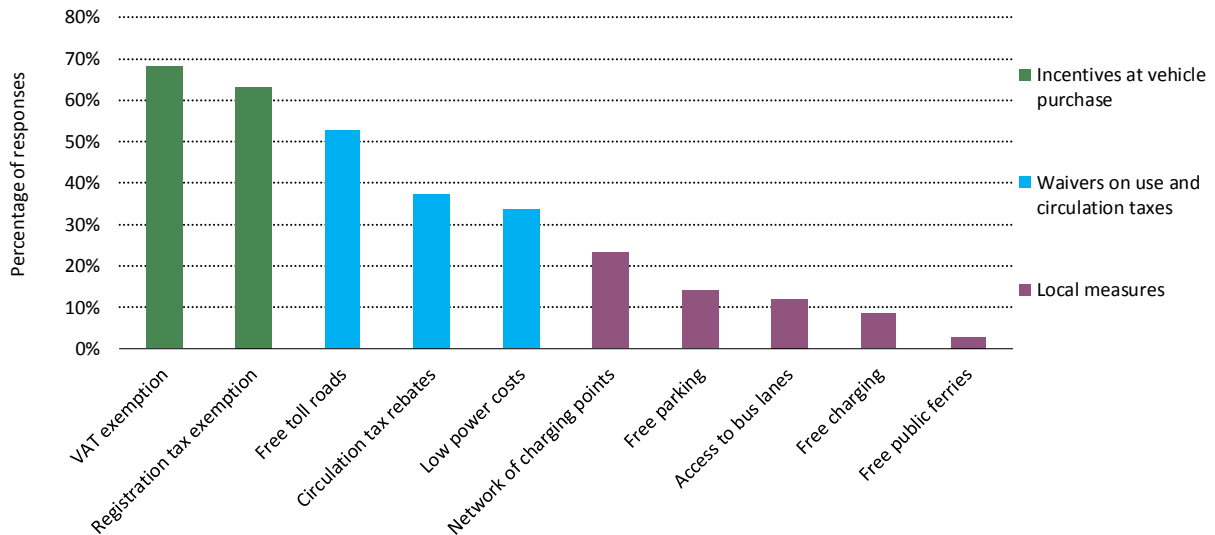


Figure 16: Perceived importance of Norway's electric car support policies based on survey results [65]

Several cases in the Nordic countries suggest that vehicles taxes differentiated based on environmental performance (fuel economy or, even better, CO₂ emissions per kilometre driven) have a positive impact on the uptake of electric cars, especially if they bring the purchase price of low- and zero-emission vehicles to the level of ICE cars. This finding is demonstrated by Figure 17, which shows that in Nordic countries (with the exception of Denmark), the market share of electric cars tends to be higher when fiscal incentives (e.g. VAT exemptions, VRT reductions and exemptions, direct subsidies and differentiated taxes) are larger and when the price gap between electric cars and equivalent ICE models is smaller.

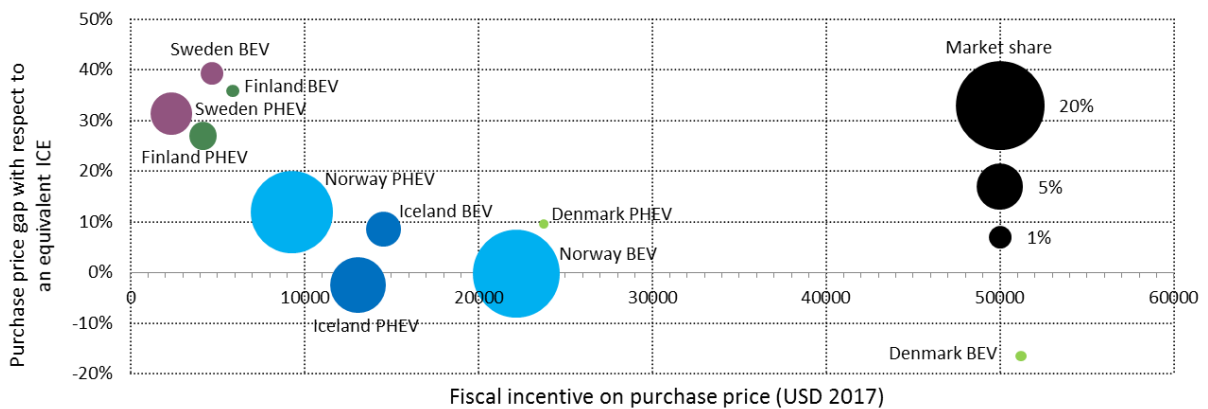


Figure 17: Purchase price incentives, price gap and market share in the Nordic countries [65]

Nonetheless, it is important to observe that the amount of fiscal incentives provided is not enough by itself to ensure the successful uptake of electric cars. The level of ambition needs to be matched with the stability in the policy framework, which has been a key element in the widespread diffusion of electric cars in Norway. On the other hand, the variance between initial announcements and following adjustments of the tax scheme for electric cars in Denmark is seen as one of the factors that hampered the market's dynamics after the decision to revise the VRT scheme in 2016 [65]. Finally, Nordic choices, and in

particular the Swedish decision to adopt a bonus/malus system for the VRT, suggest that VRT schemes can be designed to provide sufficient revenues to finance the uptake of low- or zero-emission vehicles, while avoiding being economically unsustainable for governments.

5.2.2 Findings from modeling analyses

Paper VII observes that as long as the import price of electric cars is higher than that of ICEs, the Danish VRT scheme (if not partially derogated for electric cars) amplifies the price difference, thus increasing the purchase price advantage of ICEs over EVs. Both paper VII and VIII analyse the effect of tax derogation on EVs and of bans on ICE sales on the penetration of electric cars. The analysis of paper VIII reveals that a ban on the sale of ICE cars enforced in 2025 would enable the deepest cut in GHG emissions, while regulatory measures focused on the derogation of tax would have a lower relative effect on cumulative GHG emissions reduction. Nonetheless, while evaluating the environmental performance of policy measures, it is important to consider also the variation in tax revenue that they imply. On one hand, the implementation of ban on sales/import of ICE cars enforced from 2035 onwards would lead to an increase of tax revenues, due to the penetration of taxed EVs when their investment costs have not significantly dropped yet. On the other hand, policies derogating taxes for EVs would lead to a loss of revenue for the exchequer (Figure 18). Similar findings are also obtained in paper VII, which observes that policy measures derogating taxes enable the uptake of EVs at a significant cost for the exchequer, generally higher than that from ICE bans.

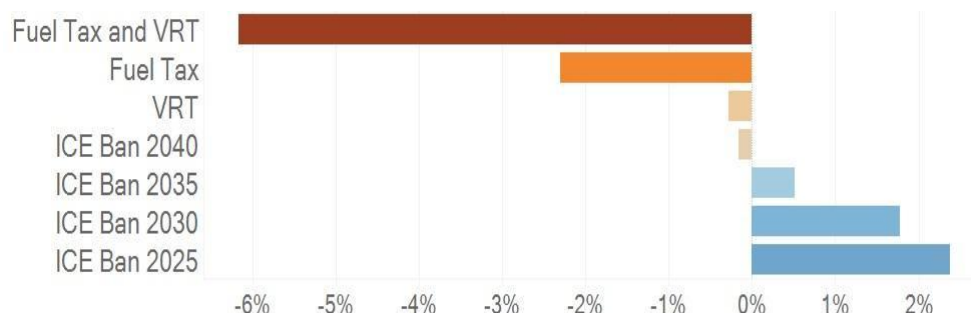


Figure 18: Actualised cumulative change in tax revenue with respect to the BaU scenario in paper VIII

Although from an environmental and tax revenue perspective the ban on sales of ICE cars enforced in 2025 is the most effective of all policies analysed, it is important to consider the different degrees of feasibility of policy implementation, stemming from their different timing, method of implementation, and public acceptability. Changes to taxation schemes require several government consultations, while the introduction of a ban of ICEs presents a challenge in terms of negotiations (on timing and exceptions) with the automotive industry, let alone the preferences of consumers. Finally, paper III suggests that BEVs need to adjust their driving patterns towards longer distances to experience a large-scale deployment.

6 Discussion on modeling approaches

Aiming at improving the representation of human behaviour in transport within BU optimization E4 models, this PhD research has developed and tested a broad spectrum of state-of-the-art methodologies, by utilising both optimisation and simulation mathematical methods. A summary of the modeling frameworks adopted in each of the models developed within the scope of this research (see Section 3) is presented in Table 3.

Table 3: Summary of the mathematical method adopted in the various models

Model	Mathematical method
TIMES-DKMS	Optimisation
MoCho-TIMES	Optimisation
TIMES-DKEMS	Optimisation
ABMoS-DK	Simulation
DCSM	Simulation
TIMES-DKMS soft-linked to DCSM	Optimisation + Simulation
ABMoS-DK soft-linked to TIMES-DK	Optimisation + Simulation

This section aims at guiding fellow researchers and modellers in the selection of the most suitable modeling framework to incorporate behaviourally realistic consumers' choice in transport within BU optimization energy system models. First, Section 6.1 describes the behavioural features characterised in the different models for improving the representation of consumers' choice in transport and discusses to which extent the approaches overcome traditional limits in behaviour representation within BU optimization E4 models. Then, Section 6.2 compares the various methodologies proposed with respect to their capability to render the behavioural features identified. Afterwards, Section 6.3 discusses the suitability of the various models to be used for diverse types of energy and transport analyses and to answer to diverse types of policy questions. Finally, Section 6.4 discusses the modeling efforts and the data requirements that the models proposed imply, and the feasibility to replicate their methodologies.

Improving the representation of consumer's choice in transport within energy system models implies the incorporation of certain behavioural features. The introduction of these features enables E4 models to explore a wider set of energy use mitigation options, combining technology improvement with behavioural change policies [11]. The models described in this thesis characterise diverse combinations of behavioural features (Table 4).

Table 4: Behavioural features integrated in the models developed

	Modal choice				Vehicle choice
Behavioural features	TIMES-DKMS	MoCho-TIMES	TIMES-DKEMS	ABMoS-DK	DCSM
Heterogeneity		✓		✓	✓
Behavioural attributes	✓	✓		✓	✓
Tangible costs		✓		✓	✓
Spatial dimension	✓	✓	✓	✓	✓
Infrastructure capacity	✓	✓			
Elastic transport demands			✓		✓

It is interesting to observe that many of the features characterised in the models developed within the scope of this thesis are those recommended by [12] to make E3 models suitable for simulating behavioural change policies. The remaining of this section describes how the behavioural features listed in Table 4 have been integrated in the different models and what is gained by integrating them.

6.1.1 Heterogeneity

Individuals' preferences constitute a fundamental aspect of decision making in the transportation sector and distinct groups of transport users are characterized by different modal adoption and vehicle purchasing preferences. Therefore, integrating population heterogeneity into the model framework is a precondition for depicting the diversity of travel behaviours across consumers. It allows the modeller to differentiate behavioural attributes across consumers and allows the policy maker to target consumer groups more effectively [47]. Without differentiating heterogeneous consumer groups, modellers are liable to an over-simplified representation of the market, which may lead to unrealistic scenarios for the modeller and ineffective policies for the policy maker.

The incorporation of heterogeneity in the transportation sector leads to a solution that is the resultant of a set of decisions taken by diverse consumers, characterized by different travel habits, perceptions and thus preferences (see Figure 12). Each group of transport users chooses its own optimal set of modes and vehicles, leading to a variety of them every year. As behaviour is an individual trait, in an ideal model, each agent would have a singular representation. However, not many modeling methods are suitable for accommodating such an ideal representation of consumers' choice heterogeneity and some trade-offs are

needed. For instance, integrating high-level population heterogeneity directly within the BU optimization E4 model would make the model's structure too complex, possibly leading to intractability. Identifying a limited number of dimensions that allows to exhaustively capture behavioural variance across the main consumer groups is crucial for this class of models. On the other hand, high-level population heterogeneity can be more easily accommodated within an external transport simulation model soft-linked to the E4 model.

Traditionally, BU optimization E4 models assume a central global decision maker that takes decisions on behalf of the average consumer, aiming to maximize the system's economic utility only accounting for levelized costs while complying with the constraints. Under these modeling assumptions, the modal shares and the technology portfolio determined by the model represent an optimal configuration for the system, but not for the consumers' perspective [21]. Moreover, such paradigm may lead to the "winner-takes-all" phenomenon, which consists in unrealistically sharp vehicle penetration patterns, whereby the cheapest technology (or mode, in case of endogenous modal shift) obtains the entire market share [32]. On the other hand, a much more realistic solution is achieved when end-users are disaggregated by classes, e.g. according to their access to technology, their level of demand and their income [67]. The rest of this section describes how this PhD research has improved the representation of consumers' heterogeneity to mimic modal choice and vehicle choice with respect to traditional BU optimization E4 models.

6.1.1.1 Heterogeneity for modal choice

The scientific literature shows that individuals' characteristics affect modal choice [21]. Therefore, transport models are normally characterized by detailed population segmentation and simulate modal choice at individual or household level [40]. This is the case for ABMoS-DK, an AB model that simulates modal choice with high-level heterogeneity outside the E4 model framework. Thanks to the AB modeling framework, the heterogeneity within ABMoS-DK is the most disaggregated of those adopted to simulate modal choice within this PhD research: it is able to differentiate the attitudes for about 370 000 agents (characterised by similar type of residential area, income level, age, car ownership, bike ownership and driver's license). On the other hand, such disaggregated population heterogeneity cannot be directly accommodated in a BU optimization E4 model. MoCho-TIMES incorporates heterogeneity directly within the BU optimization E4 model, despite more aggregated compared to the levels achievable with transport simulation models such as [40] or AB models such as [43]. Heterogeneity in MoCho-TIMES consists in 24 macro clusters of consumers, obtained by splitting the total inland passenger travel demand geographically (DKE, DKW and urban, suburban, and rural) and by socioeconomic class (in four classes of income level) into segments (Figure 19).¹⁴ Such heterogeneity manages to capture some variability of

¹⁴ Creating these segments enables the modeller to specify across groups of transport users a different perception of the attributes characterising the modes available.

modal preferences across the population, enough to overcome the “mean-decision maker” perspective [30].

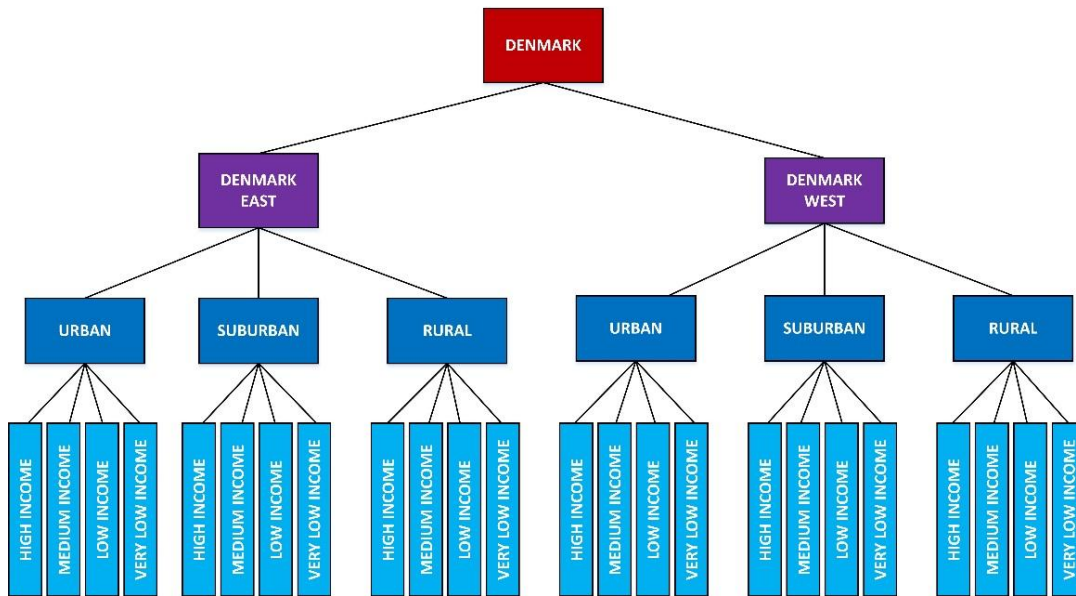


Figure 19: Schematic illustration of heterogeneous consumer groups in MoCho-TIMES

6.1.1.2 Heterogeneity for vehicle choice

Consumers’ heterogeneity for vehicle choice has been integrated in the model framework by developing the DCSM, intended to be soft-linked to the E4 model. In the consumer choice model within the DCSM, consumers are split in 18 segments characterised by similar vehicle perceptions, divided geographically (urban and rural), by driving profile (modest driver, average driver, frequent driver) and by class of innovation (early adopter, early majority, late majority), as shown in Figure 20.

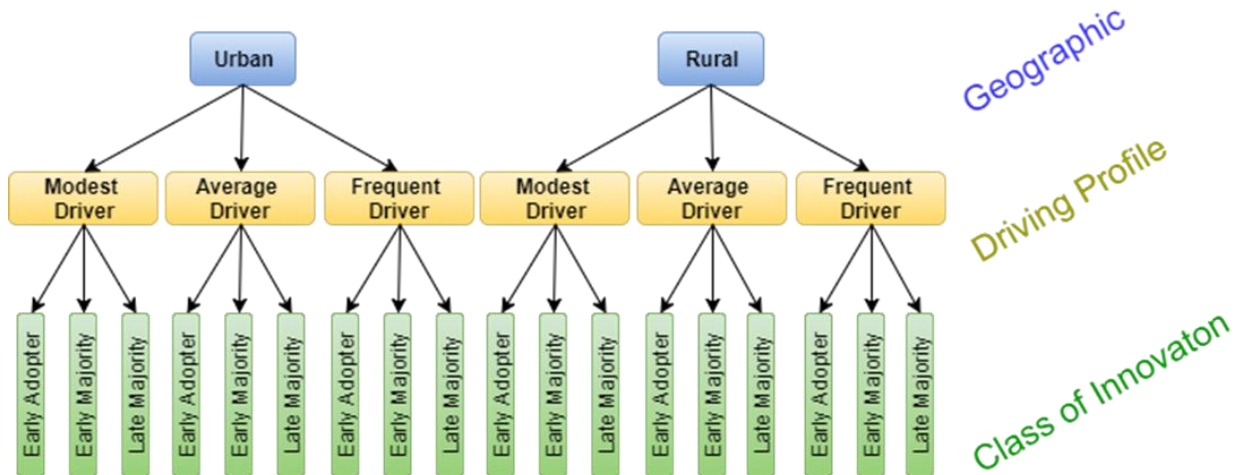


Figure 20: Schematic overview of consumer segments in the consumer choice module of the DCSM

An alternative approach that could have been used to represent the different vehicle perception across consumer groups directly within the BU optimization E4 model is that of CoCHIN-TIMES [32, 68]. This

approach splits consumers in macro classes characterised by similar vehicle perceptions and uses “clones”¹⁵ to achieve a variety of technologies fulfilling the travel demands each year, thus avoiding the “winner-takes-all” phenomenon.

6.1.2 Behavioural attributes

Consumers’ choice is driven by attributes that go beyond economic criteria (hereafter denominated “behavioural attributes”), which need to be incorporated in the model to realistically depict modal choice and vehicle choice [21, 30]. The behavioural attributes that influence consumers’ choice in transport are wide ranging and are commonly left unrepresented in traditional BU energy system models. An ideal model would simulate consumers’ choice accounting for every applicable attribute. However, it is extremely difficult to represent all relevant attributes related to modal choice [21] and vehicle purchasing decisions [30], forcing models to limit the number considered. Papers IV, VI, VII and VIII capture and quantify the perception of the behavioural attributes across the heterogeneous consumer groups via “intangible costs”.¹⁶ In those studies, intangible costs monetize the behavioural attributes via publically available empirical data, to provide an approach that is replicable for other countries with similar data availability [21, 47]. Alternatively, behavioural attributes can be represented in BU optimization E4 models as commodities, whose availability is limited to values obtained from calibration to travel surveys or to transport simulation models (see Section 6.1.2.1). This section presents and discusses, separately for modal choice and for vehicle choice, the behavioural attributes integrated in the models developed within this PhD research.

6.1.2.1 Attributes relevant for modal choice

Paper III constitutes the first effort of this PhD research to incorporate the behavioural attributes affecting modal choice in BU optimization E4 models. TIMES-DKMS accommodates just one behavioural attribute, namely travel time (the reciprocal of speed). The attribute travel time is used in combination with a TTB¹⁷ to regulate modal shift, avoiding that the mobility demand is satisfied only according to cost-optimal criteria, thus ensuring that faster but more expensive modes are also part of the solution. From a modeling perspective, the TTB is a constraint that limits the availability of the “travel time commodity”, which is consumed by all the modes and technologies when fulfilling the travel demands (see Figure 3). Despite the description of modal travel time attribute in combination with the

¹⁵ The clones are deviations from the “mean-consumer” perspective equivalent to the error term of the utility function of discrete choice models. The usage of clones has several limitations. It requires several calculations out of the model and the complexity of the model increases significantly, so that a supercomputer is required to run the model.

¹⁶ Intangible costs represent the many non-monetary perceived costs that consumers face when choosing a mode and using a vehicle. These costs are generally difficult to quantify, as their perception changes for different consumer groups.

¹⁷ The rationale of the adoption of the TTB has been provided by [69], which claims that in different geographical areas, historical periods and socioeconomic contexts people dedicate the same amount of time to mobility.

TTB enables a simple regulation of modal shift, the representation of modal choice should include a more extended set of behavioural attributes, as done in paper IV and VI. In these studies, the behavioural attributes incorporated in the models are several LoS variables related to travel-time components:

- for car: free-flow travel time, congestion time, and ferry travel and waiting times
- for public transport: in-vehicle time, departure waiting time, waiting time at the stop and walking time
- for non-motorized modes: travel time.

In paper IV and VI, the perception of these LoS attributes is captured by the intangible costs, calculated multiplying the LoS measures by the VoT. This expression of the intangible costs allows to differentiate the behavioural attributes across the heterogeneous consumer groups: the LoS depends on the geographic location (urban, suburban and rural) and the VoT is related to the income class. The intangible costs are incorporated in MoCho-TIMES in the expression of the modal cost [21] and in ABMoS-DK in the expression of the modal utility within the mode choice algorithm [43]. However, it is important to observe that intangible costs in MoCho-TIMES are very high compared to the other costs in the model (investment, O&M and fuel costs) and thus they introduce a market distortion, acting for the transportation sector within a BU optimization E4 model as an additional barrier to its decarbonisation. As observed by [30], when incorporating intangible costs into the optimization model, a higher carbon tax is required to achieve an equivalent GHG emissions abatement with respect to a traditional model. The inclusion of intangible costs in the modal cost expression makes emission reduction measures for the transportation sector more expensive and thus more unlikely to happen than in other energy sectors. To avoid this issue, it is fundamental to maintain consistency across sectors, e.g. combining the incorporation of intangible costs in the transportation sector with the inclusion of hurdle rates or intangible costs also in the other energy sectors.

6.1.2.2 Attributes relevant for vehicle choice

In paper VII and VIII the behavioural attributes affecting vehicle choice are captured and quantified via intangible costs. The behavioural attributes affecting car purchasing decisions integrated in the consumer choice component of the DCSM have been identified thanks to the literature review in [47] and are:

- model availability and risk related disutility: original equipment manufacturers (OEMs) aim at diversifying the offer of models to appeal a wider range of consumers. The higher the availability of models, the lower the intangible cost associated to it. In paper VII, the consumer segment corresponding to early adopters perceives the limited amount of models for a novel technology as a benefit, thus making the intangible cost negative.
- range anxiety and refuelling infrastructure: this term indicates the perceived penalty associated with a failure to meet a daily travel demand due to a limited battery range or limited availability

or refuelling infrastructure. Both of these attributes vary dependant on the travel profile of a consumer. The intangible cost related to range anxiety is faced only by BEVs, while that associated to refuelling infrastructure is faced by all vehicle types (despite minimal for diesel and gasoline ICEs).

6.1.3 Tangible costs

To render comprehensively the mechanisms of consumers' choice, the model should incorporate all the tangible costs perceived by the transport users. Tangible costs consist of the quantifiable monetary costs that consumers face when choosing a mode or vehicle. These go beyond the costs conventionally accounted in BU optimization E4 models (e.g. investment costs, O&M costs and fuel costs), including also ticket fares for public transport, and taxes and parking cost for private car. For vehicle choice, vehicle taxes are the most relevant tangible cost that are not normally accounted by BU optimization E4 models.¹⁸ In paper VII and VIII, vehicle taxes have been considered, accommodating them in the expression of the tangible costs within the consumer choice model of the DCSM. Tangible costs affecting modal choice have been incorporated in both paper IV and VI, despite requiring diverse levels of complexity. On one hand, ABMoS-DK easily accommodates them among the tangible costs of the motorized modes. On the other hand, BU optimization E4 models are not suitable to integrate all the intangible costs, as not all of them are fully consistent with the central decision maker's perspective. Given that the central planner does not face some of these costs, they should not be accounted in the total system cost. MoCho-TIMES has overcome such an issue by including the extra tangible costs faced by car drivers and public transport users as commodities, which are consumed by the modes in order to fulfil the travel demands (see Figure 4). The model tracks how much "tangible cost commodities" (called "perceived cost" in Figure 4) are consumed by the heterogeneous groups of transport users. In addition, consumer group-specific monetary budgets limit the consumption of the "tangible cost commodities". Further details on the integration of the tangible costs and monetary budgets within a BU optimization E4 modeling framework are provided in [21].

6.1.4 Spatial dimension

Transport implies a movement of people or goods and therefore any attempt to model its dynamics should include to a certain extent the description of the spatial context where transport occurs. The spatial dimension is especially important for simulating modal choice, as it enables to know exactly what modes are available to take a trip (based on the infrastructure available) and to compare the modal utilities. The higher the geographical disaggregation, the more precisely demand is depicted in the model and thus the more realistic is the definition of modal competition. On the other hand, a more geographically

¹⁸ Taxes are sometimes included in BU optimization E4 models when they are used for policy analyses. However, once taxes are introduced, the solution provided by the model is not a socioeconomic optimum anymore, because some regulatory distortions are introduced.

disaggregated travel demand leads to additional complexity of the model structure, which entails further modeling efforts and longer computation time. Traditional transport models describe the geographical dimension of each trip in detail through an Origin-Destination (OD) matrix, which states where each trip departs and where it ends [39]. No one of the models developed within the scope of this thesis reaches such a detailed representation of the spatial dimension, as E4 models are not used for analysing in detail transport dynamics, but rather to analyse the future evolution of the whole energy system under alternative scenarios. TIMES-DKMS and TIMES-DKEMS are the first efforts of this PhD research to incorporate the spatial dimension in E4 models. These models disaggregate inland passenger trips based on four distance categories (XS, S, M and L distance range). The spatial disaggregation in MoCho-TIMES is defined at regional level (DKE, DKW) and at type of residential location (urban, suburban and rural), in order to differentiate the LoS of the modes across geographical areas. ABMoS-DK moves a step forward with respect to MoCho-TIMES concerning the description of the geographical dimension, as it accounts for both type of origin and destination of the trips and trip length. In papers III, IV and V, the vague spatial description makes the definition of modal competition complex, thus requiring an additional modeling feature to avoid unrealistic modal shift. This is a constraint on modal travel patterns, which describes how modes contribute to meet the travel demands in different geographical locations and distance-range classes, limiting modal competition to geographical areas and distance ranges realistically covered by the modes. In particular, modal competition is regulated so that mode A can fulfil the mobility demand in a certain geographical location/distance range previously satisfied by mode B, only if both A and B cover that same location/distance range [37]. Modal travel patterns are defined consistently with the geographical disaggregation of the demand. In case this is based on trip distance, as done in paper III and V, the travel patterns can be based on the trip distance profile, which classifies the number of trips per mode and distance classes (in Figure 21 for the inland passenger transport modes in Denmark [36]).

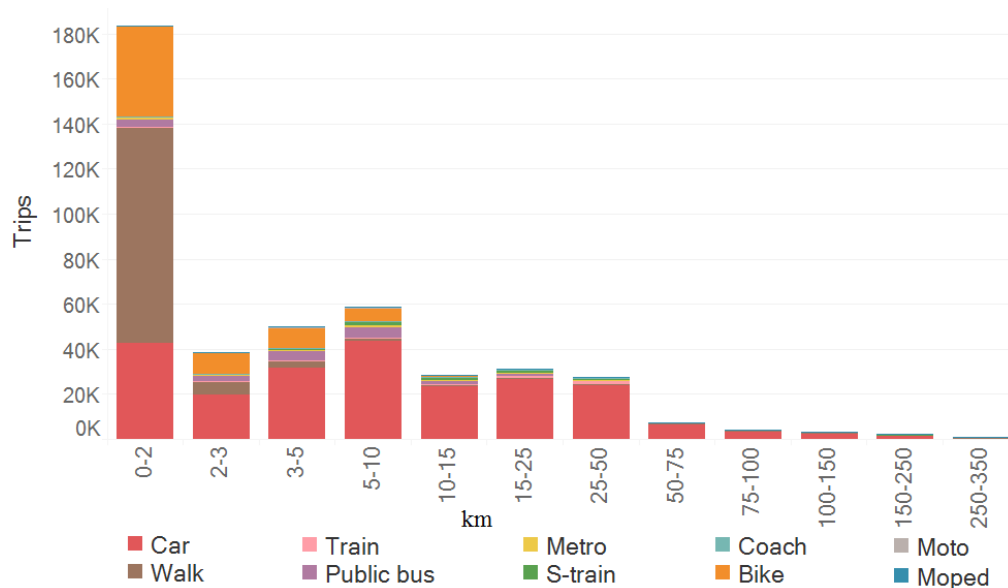


Figure 21: Trip distance profile for inland passenger modes in Denmark.

Both in this situation and in case the geographical disaggregation is based on type of urbanization (urban, suburban and rural), modal travel patterns can be obtained by the observations of a travel survey.

6.1.5 Infrastructure capacity

Transport infrastructure is a key driver of mobility demand and modal choice [6, 70]. Transport simulation models account for the capacity of the road network and its effect on travel time, congestion time and thus modal generalized costs [40]. However, energy system models rarely represent transport infrastructure [12]. The rationale for incorporating this feature in E4 models is that it enables to regulate modal shift, because there must always be enough infrastructure capacity to accommodate the mobility demand. The existing infrastructures are sufficient to accommodate the current levels of mobility demand, but as mobility demand increases the existing infrastructures could saturate. Then, investments in additional infrastructures capacity are required, which involve a cost for the system. Therefore, infrastructure requirements regulate modal shift, as a considerable shift between modes may end up in infrastructure saturation, subsequently requiring investing in additional infrastructure capacity. Paper III and IV integrate five types of transport infrastructure: road, three railways for train, S-train and metro and bicycle lanes. These transport infrastructures are not represented explicitly in the model, but as commodities that the modes consume in order to fulfil the mobility demand (see Figure 3). A detailed description of the approach used to integrate infrastructure capacity in the models is provided in [37].

6.1.6 Elastic transport demands

A review of energy system models observed that, among the modal choice modeling approaches reviewed, none was based on cross-price elasticities, which would be an easy way of simulating modal shift as a result of price changes [12]. Within the scope of this PhD research, the use of substitution elasticities to simulate modal shift has been tested in paper V.¹⁹ In TIMES-DKEMS, the modal travel demands composing an aggregate (a distance range class of travel demands, i.e. XS, S, M and L) adjust their levels in reaction to changes of their shadow prices relative to a reference scenario [41]. The values of the elasticities control the magnitude of modal demand variation given a certain travel cost change. In addition, the aggregates conserve their total volume after substitution. The identification of the proper values for the substitution elasticities to be used in TIMES-DKEMS is quite challenging, because the elasticities available in the literature cannot be used directly in the novel modeling framework [41]. The reason is that the values of substitution elasticities adopted should always be consistent with the travel costs defined in the model, which are different between TIMES-DKEMS and transport simulation models. In the first model, travel costs for car and public transport include levelised investment, O&M and fuel costs. On the other hand, in transport simulation models normally travel costs for car include O&M costs and fuel cost, and travel costs for public transport include the transit fare. Given this difference in the

¹⁹ Direct price elasticities have not been utilized for mobility demands in any of the models developed.

travel costs definition across model types and thus the impossibility to use values directly from the literature, the transport elasticities used in TIMES-DKEMS are based on the modeller judgment.

Concerning vehicle choice, in paper VII the CarSTOCK model within the DCSM uses gross national product (GNP) and fuel prices projections linked with income and fuel elasticities of demand to calculate the future size and activity of the car stock.

6.2 *Models' capability to depict the behavioural features*

The models developed within this PhD research are characterised by different capabilities to depict the behavioural features listed in Table 4. A qualitative evaluation of the level of realism achieved by the different models in the representation of the behavioural features is presented in Table 5.

Table 5: Models' performances depicting the behavioural features identified

	TIMES-DKMS	MoCho-TIMES	TIMES-DKEMS	ABMoS-DK	DCSM
Heterogeneity		++		+++	++
Behavioural attributes	+	++		+++	++
Tangible costs		++		++	+
Spatial dimension		+		++	+
Infrastructure capacity	+	+			
Elastic transport demands			++		+

Notes: The performances of the models concerning the representation of the behavioural features are determined with respect to TIMES-DK. The comparison is qualitative: +++: significant improvement; ++: major improvement; +: minor improvement.

Regarding heterogeneity, the most detailed representation is achieved in ABMoS-DK. The AB approach adopted for this model enables to achieve an extremely disaggregated description of transport users, which are represented by about 370 000 agents. MoCho-TIMES follows, with the transport users split in 24 segments. TIMES-DKMS and TIMES-DKEMS do not improve the representation of heterogeneity with respect to the backbone model and maintain the “mean-decision maker” perspective. The DCSM improves the behavioural realism of car choice splitting transport users in 18 segments. Concerning the integration of the behavioural attributes, ABMoS-DK performs the best among the models developed. It incorporates the same LoS attributes as in MoCho-TIMES, plus it keeps track of car ownership and possession of driving licence among agents to determine if car is or not an available mode for each agent in the mode choice algorithm. In addition, it tracks the age of the agents to differentiate the perception of bike. TIMES-DKMS only integrates one behavioural attribute, namely speed. In the DCSM, vehicle choice is determined accounting also the perception of three behavioural attributes: model availability, range anxiety and refuelling infrastructure. ABMoS-DK and MoCho-TIMES incorporate the same tangible costs, but the main difference between the two models lies in the complexity of incorporating this feature, as explained in Section 6.1.3. The DCSM includes more comprehensive

tangible costs, by comprising also car taxes and insurance cost. The most detailed spatial description has been achieved in ABMoS-DK, which accounts for both type of origin and destination of the trips and trip length. The spatial dimension is vaguer in MoCho-TIMES, which disaggregates the inland passenger travel demand according to the type of urbanization (urban, suburban and rural) from which trips start, while in TIMES-DKMS and TIMES-DKEMS it is identical to the one defined in TIMES-DK. Infrastructure capacity has been incorporated just in MoCho-TIMES and TIMES-DKMS and in a simple way, limiting the amount of mobility demand that can shift without requiring to invest in new infrastructure capacity. The approach used to incorporate this feature represents a first effort and possible further improvements are discussed in Section 7. Finally, elastic transport demands are integrated in TIMES-DKEMS in the form of linearized elasticities of substitution to simulate modal shift and in the DCSM to project the size and activity of the car stock.

6.3 Suitability to answer to policy questions

The type of analyses to be performed and, ultimately, the policy questions to be answered play an important role in the choice of the model framework [30]. Diverse approaches are more or less suitable to different types of analyses and policy questions, and the appropriate choice is important to ensure the reliability of the results and to avoid superfluous modeling efforts. This section aims at guiding fellow researchers in the choice of the most suitable modeling framework (among those evaluated within this PhD research) to answer several policy questions within the scope of transport and energy. Table 6 presents some examples of analyses and policy questions and discusses if they can or cannot be addressed with the various methodologies developed.

Table 6: Suitability of different models to answer to some policy questions

	TIMES-DK	TIMES-DKMS	MoCho-TIMES	TIMES-DKEMS	ABMoS-DK	DCSM	ABMoS-DK soft-linked to TIMES-DK	TIMES-DK soft-linked to DCSM
1. Which and how much fuel will be consumed by the inland passenger transportation sector in the future considering technology improvement measures?	✓	✓	✓	✓			✓	✓
2. Which and how much fuel will be consumed by the inland passenger transportation sector in the future considering both technology improvement and behavioural measures?		✓	✓	✓			✓	✓
3. What is the optimal use of domestic biomass potential across energy sectors?	✓	✓	—	—			✓	✓
4. Which and how much fuel will be consumed by the car sector in the future considering the technological characteristics of the available options?	✓	✓	✓	✓			✓	
5. Which and how much fuel will be consumed by the car sector in the future considering real consumers' perceptions of the options available?						✓		✓
6. How do changes of taxation scheme influence the size of cars purchased?						✓		✓

Table 6: Suitability of different models to answer to some policy questions

	TIMES-DK	TIMES-DKMS	MoCho-TIMES	TIMES-DKEMS	ABMoS-DK	DCSM	ABMoS-DK soft-linked to TIMES-DK	TIMES-DK soft-linked to DCSM
7. What is the contribution of endogenous modal shift to cut CO ₂ emissions?		✓	✓	✓			✓	
8. What is the optimal level of shift away from car?		✓	✓	✓				
9. How does a CO ₂ reduction target affect modal shares?		✓	✓	✓				
10. Which consumer groups are the most and least willing to shift away from car?			✓		✓		✓	
11. How do changes to car's congestion time affect CO ₂ emissions?			✓		✓		✓	
12. How does willingness to dedicate more time to travel influence modal shift?		✓	✓		✓		✓	
13. How do changes of parking fees affect modal shares?			✓		✓		✓	
14. How do changes of taxation scheme influence modal shares?		✓	✓	✓	✓		✓	
15. How do alternative urbanization trends affect modal shares?			✓		✓		✓	

Table 6: Suitability of different models to answer to some policy questions

	TIMES-DK	TIMES-DKMS	MoCho-TIMES	TIMES-DKEMS	ABMoS-DK	DCSM	ABMoS-DK soft-linked to TIMES-DK	TIMES-DK soft-linked to DCSM
16. In which geographical areas is it easier to shift away from car?			✓		✓		✓	
17. How do investments in transport infrastructure affect modal shares?		✓	✓					
18. What is the contribution of car sharing to cut CO ₂ emissions?		✓	✓	✓	✓		✓	
19. What is the contribution of autonomous cars to cut CO ₂ emissions?			✓		✓		✓	

Note: ✓ means that the model is suitable to perform that analysis and to answer to that policy question.

The backbone model TIMES-DK was only able to evaluate GHG emissions reduction from techno-economic policy measures (such as 1, 4 in Table 6), while it was not able to analyse the potential GHG emissions reduction from policies affecting consumers' behaviour (e.g. 2, 5). In order to analyse the effectiveness of policy measures affecting consumers' perception, it is necessary to adopt one of the models proposed in this thesis. To carry out cross-sectoral analyses (e.g. 3), the representation of consumers' behaviour is not a requirement, but instead it is necessary to adopt a modeling framework that represents the whole energy system. For this type of analyses MoCho-TIMES and TIMES-DKEMS cannot be used at the current stage, as they represent only the transportation sector standalone. Once integrated with the rest of the energy system, these models could serve for cross-sectoral analyses, despite some additional efforts are required with MoCho-TIMES to tackle the market distortion introduced by intangible costs (as explained in Section 6.1.2.1). ABMoS-DK can be used for cross-sectoral analyses only if soft-linked to the E4 model representing the entire energy system. In order to analyse the development of the car sector considering the techno-economic characteristics of the options available (e.g. 4), TIMES-DK is sufficient. However, a more comprehensive analysis of this sector entails considering also real consumers' perceptions (e.g. 5, 6), which go beyond the scope of analysis of traditional BU optimization E4 models. For this type of questions, a more suitable approach is to use an external car stock model equipped with consumer choice model, as the case of the DCSM. If it is necessary to evaluate the evolution of the car stock within a larger framework that includes the whole energy system, the car stock model and the E4 model should be soft-linked. For analyses exploring the role of modal shift to reduce the CO₂ emissions from the transportation sector in the long-term (e.g. 7 - 9) several approaches can be adopted and the most suitable approach to be used should be evaluated from case to case. When modal shift dynamics need to be explored at consumer group level (e.g. 10), both MoCho-TIMES and ABMoS-DK are effective (the latter enables a more disaggregated analysis of modal shift dynamics). However, ABMoS-DK is only useful to determine the effect of policy measures on modal shares and, via soft-linking with TIMES-DK, on the rest of the energy system. When modal choice is out of the scope of analysis, ABMoS-DK is superfluous. Moreover, ABMoS-DK does not account GHG emissions and it needs to be soft-linked with the backbone model to consider this aspect. When it is desirable to test the effect of alternative outcomes for behavioural attributes driving modal choice (e.g. 11, 12), MoCho-TIMES can be used, despite it reaches a lower detail level than ABMoS-DK. To analyse the effect of changes to parking prices on modal shares (e.g. 13, 14), both MoCho-TIMES and ABMoS-DK are suitable. If in turn the effect on fuel consumption and GHG emissions from the transportation sector is to be evaluated, ABMoS-DK must be soft-linked to the backbone mode, while MoCho-TIMES is already sufficient. Either MoCho-TIMES or ABMoS-DK must be adopted to test the effect of urban policy measures on modal shares and to analyse the influence of urbanization trend on fuel consumption (e.g. 15,

16). Any analysis focused on transport infrastructure (e.g. 17) should be performed using either TIMES-DKMS or MoCho-TIMES, which are the only two models incorporating such feature.

TIMES-DKMS and TIMES-DKEMS should be the preferred option when the purpose of the study is to analyse modal shift dynamics at aggregated level, because their approach is the simplest to reproduce (see Section 6.4). However, in these models modal shift is only regulated by few variables, which translates in the possibility to perform less policy analyses and with less disaggregated results with respect to the other models. In general, when a model is not used to inform policies affecting human behaviour, a less detailed representation of consumers' choice is sufficient. In this case, the methodologies described in paper III, IV and V for simulating modal shift directly within BU optimization E4 models are suitable. On the other hand, when a model is used for testing policies affecting both technological development and consumers' choice, a more suitable modeling framework consists in soft-linking the BU optimization E4 model with a transport simulation model that accounts for the behavioural features in transport (as in paper VIII and [51]).

6.4 Modeling efforts, requirements and model reproducibility

RQ 11

The previous sections explain that the models proposed include different combinations of behavioural features (Section 6.1), that they depict such features with different degrees of realism (Section 6.2) and that they are suitable to perform different types of analyses (Section 6.3). In order to give to fellow researchers aiming at improving the behavioural realism of consumers's choice in E4 models a comprehensive overview, it is also important to consider the modeling efforts, the requirements and the reproducibility that the different models entail. This discussion is carried out in the remaining of this section by comparing the models with respect to five key aspects: data requirement, softwares requirement, mathematical method, soft-linking requirement and model structure's complexity.

6.4.1 Data

All the models developed within this PhD project require an extended amount of data. Table 7 compares the models equipped with endogenous modal shift developed within the scope of this PhD research with respect to data requirement.²⁰ Generally, the more parameters are needed to depict consumers' behavior, the more data is needed and the more calculations outside of the model are necessary for processing such data as required by the model.

²⁰ The data necessary to develop the DCSM is not discussed in Table 7 because that is the only method developed within the scope of this PhD research to improve the representation of vehicle choice and thus it cannot be compared with the other approaches. The data requirement to develop the DCSM includes projections of technical specifications (e.g. fuel economy, mileage, lifetime) and of tangible costs (e.g. investment cost and O&M cost) for each car type and engine size, socioeconomic data (GDP projections, residential area and age), elasticities, the vintage of the existing car stock, amount of car models available and availability of recharging infrastructure. Due to the high amount of data required to develop the DCSM, the qualitative evaluation for this model in Table 7 is 1.

Table 7: Data requirements for the models equipped with endogenous modal shift

	TIMES-DKMS	MoCho-TIMES	TIMES-DKEMS	ABMoS-DK
OD matrix		✓		✓
VoT		✓		✓
LoS		✓		✓
Trip purpose				✓
Trip length				✓
Departure time				✓
Speed (travel time)	✓	✓		✓
TTB	✓	✓		
Modal travel patterns	✓	✓	✓	
Car ownership				✓
Socio-demographics				✓
Infrastructure	✓	✓		
Elasticities			✓	

A transport simulation model consistent with the geographical scope of the E4 model can be used to get the OD matrix, the VoT data, and data and mathematical expressions for the LoS attributes. For Denmark, such a transport simulation model is LTM [39, 40]. This kind of model is not only available for Denmark, but also for some other countries, especially but not limited to European countries [71 - 73]. A travel survey consistent with the geographical scope of the E4 model can provide data on trip purpose, trip length, departure time, speed, TTB, modal travel patterns and car ownership. For Denmark, the travel survey adopted is TU survey [36]. Fortunately, travel surveys are available for several urban areas, regions and countries around the world [43, 74]. Socio-demographics provide socioeconomic and demographic information on the transport users and should be widely available from any national statistics. Infrastructure data includes both data on the networks' capacity utilization levels and on costs.²¹ This kind of information should be available from the national office dealing with road traffic, from railway companies and even from national statistics. In case data on status and costs of transport infrastructures are not easy to recover, an alternative approach to represent the requirements of transport infrastructure can be adopted, as explained in [31]. Concerning elasticities, there is not much literature on substitution elasticities for modes other than public transport and car. Moreover, the elasticities used in TIMES-DKEMS are based on a definition of travel costs that is different from that in transport simulation models,

²¹ Infrastructures' capacity utilization levels specified in paper III and IV are geographically aggregated and lack of temporal detail. Increasing the time granularity of the mobility demand (e.g. night and peak-hour times) would enable characterising the intra-annual and intra-day variability of the utilization levels of the infrastructure. This process entails a significant effort for recollecting the data, which is justifiable only if disaggregated transport analyses need to be carried out. However, for such type of analyses, transport simulation models (such as LTM for Denmark [3839]) are more suitable.

thus elasticities from the literature cannot serve for our scope (see Section 6.1.6). The identification of the proper values for such elasticities is not an easy task and the modeller needs to critically evaluate the elasticities in the literature before using them within the TIMES model.

Models comparison with respect to data requirement (Table 7) reveals that TIMES-DKEMS is the model that needs the least data to introduce some degree of behavioural realism in transport in BU optimization E4 models. For TIMES-DKMS, the main source for the extra data required is the national travel survey. MoCho-TIMES and ABMoS-DK require a more extended amount of data with respect to the other models (despite achieving a better behavioural representation). These models need both a national travel survey and a transport simulation model. In particular, the latter works as a support model that defines trip distribution and characteristics in the region under assessment, modal LoS and their perception by transport users.

6.4.2 Softwares

The choice of adopting an endogenous or soft-linking approach to incorporate the behavioural features in the model influences the softwares requirement. When an endogenous approach is chosen (e.g. the classical structure of the model is adjusted or the original code of the model is edited to integrate the additional features) the software that was already used to develop and run the backbone E4 model (e.g. VEDA for TIMES models) is sufficient to develop and run also the new E4 model that incorporates consumers' choice. On the other hand, when the E4 model is soft-linked with an external model that includes the behavioural dimension (soft-linking approach), the latter model might need to be developed and run with another software. This case implies both additional costs for purchasing the licence and the software and wider (or more skilled) staffs capable of handling different modeling environments to develop, maintain and use the various models available. This is the case of ABMoS-DK, which requires different modeling skills with respect to BU optimization E4 models, since it is developed and simulated using AnyLogic multimethod simulation tool [75]. However, the external model can also be developed and run using more widespread and known softwares. This is the case of the DCSM, which is a spreadsheet model based on Excel.

6.4.3 Mathematical method

Simulation models describe the development of a system based on its logical representation and on exogenously defined assumptions, while optimization models apply mathematical programming to determine the optimal configuration of the system subject to some constraints [76]. Models based on the simulation method can easily include detailed population heterogeneity, the wide set of attributes that drive consumer's choice and accommodate non-linear functions suitable to mimic it. They simulate modal and vehicle choice realistically, presenting a solution that reflects consumers' preferences and acceptance, although such solution might not be cost optimal. On the other hand, models based on the optimization

method identify a cost-optimal solution, without necessarily reflecting real consumers' perceptions. Optimization models might lead to unrealistic solutions, such as the emergence of the "winner takes all" phenomenon [32, 68]. This phenomenon can be avoided, but at the cost of including several constraints and increasing the complexity of the model structure. Simulating realistic consumers' choice in transport directly within optimization models requires an effort that generally is not corresponded by the quality of the results achieved. On the other hand, a high degree of realism of consumers' choice can be achieved in a simulation model, which can easily accommodate MNL, CES, AB and other modeling frameworks suitable for rendering human behaviour. Given this background, ABMoS-DK and the DCSM, which are based on the simulation method (see Table 3), are more suitable at incorporating the behavioural features than the models developed using the TIMES model paradigm (based on optimization method).

6.4.4 Soft linking

This PhD research has developed and tested two model soft-linkings: that between TIMES-DKMS and the DCSM (Section 3.4.1) and that between ABMoS-DK and TIMES-DK (Section 3.4.2). The first multi-method framework falls in the independent model convergence class, while the second belongs to the partial integration category [11]. The proper procedure for soft-linking models requires the harmonization of all assumptions and databases across models to avoid inconsistencies. Moreover, for partial integration soft-linkings, a model's outputs need to be suitably transformed before being input in the other model (e.g. aggregated, disaggregated, scaled, etc.). And such operations on the model's outputs need to be replicated as many times as the iterations needed to make the models' results converge. In case the number of iterations is limited, data exchange between models can be done manually, although this requires time and could lead to mistakes. In case many iterations are needed, it might be convenient to develop a tool that automatizes the process, speeding up the data exchange. In both cases, soft-linking models requires an additional effort with respect to using a unique modeling framework. On the other hand, the soft-linking approach makes the model more flexible: whenever the analysis does not require insights on human behaviour in transport, the E4 model can be run in standalone mode, with a simplified representation of the transportation sector. Considering this discussion, ABMoS-DK and the DCSM, which are intended to be soft-linked to the BU optimization E4 model, imply additional modeling efforts.

6.4.5 Model structure's complexity

Integrating consumers' choice in transport directly within the BU optimization E4 model (endogenous approach) allows to determine optimal decarbonisation pathways as a combination of technological improvements and behavioural change without relying on external models soft-linked (see Section 6.4.4). Nonetheless, in order the E4 model to accommodate the behavioural features, it is required either to change the code of the core model or to develop a more complex model structure. The first is the case of TIMES-DKEMS, which adopts a novel version of the TIMES code with linearised elasticities of

substitution to mimic modal shift [42]. Despite TIMES-DKEMS requires to use the novel version of the TIMES code, this approach limits the complexity of the model structure. The latter case, which is valid for TIMES-DKMS and for MoCho-TIMES, integrates the behavioural features at the cost of a more complex structure of the transportation sector (as visible comparing Figure 2 with Figure 3 and Figure 4). Higher model structure's complexity consists in additional modeling efforts, which generally imply longer computational times to determine the solutions and more complexity in analysing and interpreting the model's results. The structure of MoCho-TIMES is more complex than the one of TIMES-DKMS, mostly due to the introduction of heterogeneity and intangible costs. Moreover, the fact that intangible costs introduce a market distortion in optimization models that increases the marginal abatement costs of CO₂ emissions in the transportation sector (discussed in Section 6.1.2.1) implies that, in order MoCho-TIMES to be integrated within the E4 model of the whole energy system, it is necessary to introduce also in the other energy sectors hurdle rates or intangible costs able to levelize the CO₂ marginal abatement costs across sectors. Based on this discussion, TIMES-DKMS and to a larger extent MoCho-TIMES imply additional modeling efforts compared to the other models developed within this PhD research.

6.4.6 Reproducibility and usability

Despite all the methodologies developed and tested within this PhD research aim at integrating transport behaviour within TIMES-DK, lastly the intention is to produce methodologies replicable in any BU optimization E4 modeling framework. A qualitative evaluation of the different models developed within this research according to their modeling efforts and requirements is provided in Figure 22. Since less modeling efforts imply a higher grade in Figure 22, the wider the area associated to a model, the easier reproducing that model is.

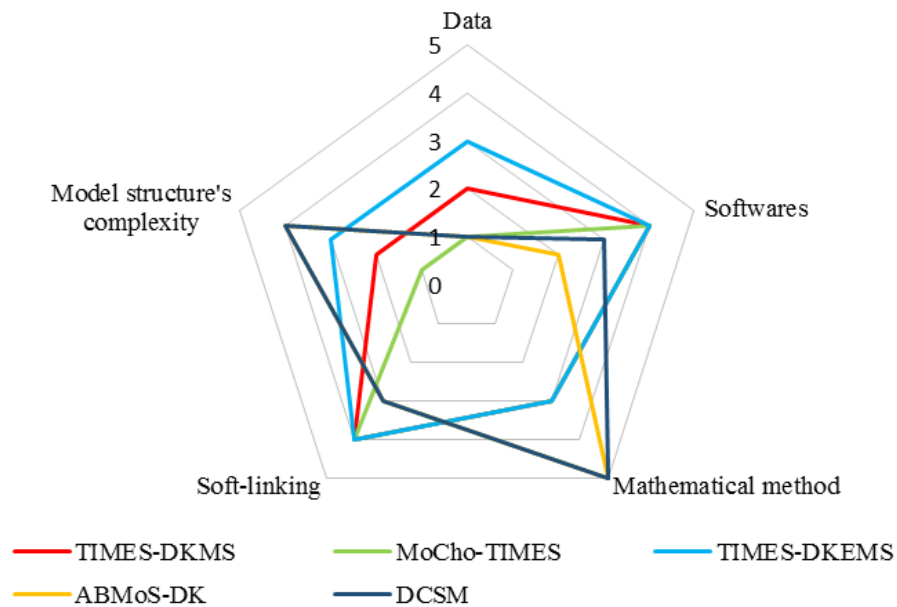


Figure 22: Requirements to reproduce the models

Notes: the comparison of the modeling efforts and requirements in this figure is qualitative. The scale is from 1 to 7, where 1 is the lowest grade, corresponding to a significant higher effort compared to TIMES-

DK, 4 corresponds to an effort equivalent to the one of TIMES-DK and 7 is the highest grade, corresponding to a significant improvement with respect to the backbone model.

Based on the modeling efforts and requirements of the different methodologies discussed so far in this section, among the methodologies that enable to simulate modal shift the one used in TIMES-DKEMS seems the easiest to reproduce. Data requirement for TIMES-DKEMS includes only elasticities and modal travel patterns. Besides, the model can be developed using a publicly available new version of the TIMES code, without needing to soft-link with an external model, nor to sophisticate the model structure. ABMoS-DK performs better than TIMES-DKEMS concerning the mathematical method and model structure's complexity, but it is extremely data intense, it requires an extra software and to develop the soft-linking procedure. TIMES-DKMS implies similar modeling efforts to TIMES-DKEMS, except for requiring some extra data and resulting in a slightly more complex model structure. MoCho-TIMES requires even more data and is characterised by a more complex structure than TIMES-DKMS. Finally, the DSCM performs fine concerning the mathematical method adopted and the model's structure complexity, while its main drawback lies in the extensive data requirement (although most of the data used for its development is open source).

7 Further research

Each of the papers produced in this PhD research proposes topics that should be analysed and aspects of the models that could be improved through further research. Some of the modeling improvements suggested in the first papers (e.g. paper II and III) have been tackled along the PhD work, while some others still need to be improved. This section first presents to fellow researchers alternative modeling approaches and improvements to the methodologies already developed to mimic consumers' choice in E4 models. Then, it suggests some interesting topics that could be explored and analysed using the models developed within this PhD research.

7.1.1 Modeling

Due to the intrinsic nature of TIMES model generator, all endogenous methodologies (those developed within the E4 framework) are characterized by perfect-foresight, which is an assumption far from reality. Myopic optimization, in which the window of foresight is limited to a period shorter than the model's time horizon, can improve the simulation of modal adoption and vehicle purchasing decisions by depicting consumers' nearsightedness. The scientific literature has shown that different levels of foresight adopted affect models' results [77]. The use of myopic optimization in the TIMES model framework to capture imperfect and limited foresight of decision makers should be explored by further research, especially considering that the myopic version of TIMES is available [35]. Another improvement recommended relates to the fact that in all the models proposed within this thesis, end-users are characterized by perfect-information and perfect-rationality. Even in most transport simulation models, utility maximization, perfect-rationality and perfect-information are the underlying assumptions for simulating modal choice. However, these assumptions are not realistic, because choices are biased from optimality in many aspects. Evidences from behavioural economics suggest that choice mechanisms in transport are more complex than described by current transport models [78, 79] and advocate a more extended use of insights from travel behaviour to improve the representation of consumers' choice in transport models. The methodologies developed within this PhD research could be further developed to incorporate also other

variables affecting consumers' choice. An alternative approach to incorporate modal choice in E4 models that could be tested by fellow researchers consists in the use of multi-objective analysis. Despite this approach cannot be directly implemented in current TIMES models and would require the development of an ad-hoc modeling framework, it seems suitable to represent decision making based on multiple criteria, where a conflict between alternative objectives exists: reducing total system costs and maximizing the utility of consumers. The model would simultaneously optimize two distinct objective functions: on one hand it would minimize total system costs as perceived by the central decision maker (the costs traditionally included in the objective function of optimization E4 models) and on the other hand it would maximize the utility (i.e. a function obtained as reciprocal of the intangible costs) of transport users. This model set-up could also facilitate the inclusion of the additional external costs often adopted in policy cost-benefit analyses [80]. Another issue that future research could address is the improvement of the representation of transport infrastructure, in particular the modeling of the relationship between infrastructure capacity utilization and travel speed, as proposed by [13]. Higher road capacity utilization reduces cars' speed, which might be mitigated by investments in additional infrastructure capacity. Conversely, a lack of capacity expansion results in lower cars' speed, which might induce modal shift away from car. Improving the representation of transport infrastructures could allow the model to choose between investing in capacity expansion to increase modal speed or rather maintaining the current capacity at lower speed. The description of a possible procedure to model these dynamics is illustrated by [31].

7.1.2 Analyses

Once consumers' choice is integrated within the BU optimization E4 model framework, several new scenario and policy analyses can be performed with respect to traditional models. This section only suggests new interesting analyses that have not been performed in any WP belonging to the COMETS project. The models that enable endogenous modal shift seem promising to explore the potential penetration of increasingly recurring phenomena like car sharing, carpooling and mobility-as-a-service (MaaS) systems and their potential contribution to reach low-carbon transportation sector and energy system [81]. Car sharing could be represented as a new car technology characterized by a higher mileage per year, while carpooling could be represented by a new car technology with higher occupancy factor. Finally, MoCho-TIMES and ABMoS-DK seem suitable models to study the conditions for the adoption of autonomous cars in Denmark and the effect of their penetration on the whole energy system²². Autonomous cars could be represented as a new car technology characterised by a higher investment cost than conventional cars (due to the presence of several innovative electronic equipments) but lower VoT. Shared autonomous cars could be represented as well, via a technology with the same characteristics as

²² To analyse the effect autonomous cars on the whole energy system, the two models would need to be linked with TIMES-DK, which represents the whole energy system.

the private autonomous car but with higher mileage and/or occupancy factor and with associated a fare. Once these new modes are described in the model, a sensitivity analysis should be performed to assess for which combinations of mileage, occupancy factor, investment cost, fare and VoT autonomous cars enter the market and how they affect fuels consumption and GHG emissions.

E4 models' results are meant to support decisions taken by policy makers and energy planners, hence it is important to check the robustness of the models' results to the uncertainties of the input parameters. In order to address the uncertainties inherent to long-term energy system analysis, most of the studies conducted with E4 models (including those carried out within the scope of this thesis) explore alternative scenarios describing storylines of plausible futures.²³ However, for these approaches on one hand the identification of the key uncertainties is mostly based on the modeller's judgments, who might omit capturing relevant parameters, and on the other hand the number of uncertainties taken into account is generally limited [82, 83]. Further research should tackle this limit, informing policy makers on the robustness of the solutions provided by E4 models. For this purpose, a global sensitivity analysis with Morris screening followed by a statistical evaluation of the uncertainty propagation through Monte Carlo method could address the uncertainty of exogenous inputs when using E4 models for long-term energy system analysis while maintaining the resolution of the problem deterministic and limiting the computation time.

²³ Besides scenario analysis, uncertainties in E4 models are mostly dealt with local sensitivity analyses, stochastic programming, robust optimization and fuzzy programming.

8 Conclusions

This PhD thesis contributes to the scientific progress in the field of energy system models addressing an important weakness of bottom-up optimization E4 models, which is the poor representation of consumers' choice in transport (see Section 2). The PhD research has developed several state-of-the-art methodologies to integrate modal choice and vehicle choice within energy system models (see Section 3). The novel methodologies enable to analyse the potential contribution to GHG emissions reduction of technology switch and technological improvements in combination with changes in travel behaviour in a unique E4 modeling framework, comprehensive of the whole energy system. The PhD work constitutes a significant improvement in the field of E4 models and makes them suitable for a wider range of applications in scenario and policy analysis compared to traditional E4 models. It inaugurates the possibility to adopt bottom-up optimization E4 models to analyse decarbonisation pathways considering both the behavioural and technological dimensions, thus enhancing their credibility for policy evaluation in the transportation sector. The original modeling frameworks developed within the scope of this thesis enable to analyse more comprehensive scenarios, sensitive to both technology and behavioural variables, thus being suitable both to involve relevant stakeholders in the public debate on decarbonisation strategies [54] and to support policy makers in the choice of effective measures to reach the environmental targets [37, 50]. The analyses conducted with the novel models developed within the scope of this PhD research indicate that modal shift would contribute to achieve carbon-neutrality in the Danish transportation sector at faster pace and with lower cumulative GHG emissions than considering a merely “technology fix” strategy [37] (see Section 4). However, authorities have a key role in promoting modal shift away from cars towards non-motorized and public modes of transport [21]. A significant shift away from private cars is possible, although it requires a very ambitious policy package inclusive of substantial investments in new public transport infrastructure, improvements to the level-of-service of public transport, incentives for the adoption of public transport and increased registration tax and ownership tax for private cars [43]. In particular, the modeling analyses identify that wealthier consumers and consumers living in rural areas are

more reluctant to shift away from car transport [21]. Considering the difficulties in achieving a major shift away from private cars, this mode is likely to maintain the highest modal share also in the future. Hence the need to couple the support to modal shift with the electrification of the car sector (combined with the decarbonisation of the power grid) in order to comply with the Danish environmental targets [50]. Moreover, a holistic analysis reveals that the compliance with the target of fossil-free Danish energy system by 2050 would lead to cumulative GHG emissions in 2050 in line with a national contribution to a global temperature rise of 1.75-2°C [50]. Based on the results of the analyses carried out with the novel models and considering best practices in the Nordic region [65], this thesis provides policy recommendations on the measures that authorities should put in practice to foster modal shift away from car to more sustainable modes of transport and to encourage the uptake of electric cars (see Section 5). Thanks to the broad range of methodologies developed and tested within the scope of this PhD research to incorporate consumers' choice in transport within bottom-up optimization E4 models, this thesis can help fellow researchers and modellers willing to include behavioural realism of transport users' in energy system models in the selection of the most suitable approach considering several criteria (see Section 6). It does so in three steps: first, this thesis describes the features that enable to incorporate consumers' behaviour in transport within the model framework and compares the capability of the different models developed to render such features. Then, it discusses the ability of the different models to answer to several types of policy questions and, lastly, it describes the modeling efforts and the requirements that reproducing the models entail. Finally, this thesis suggests possible directions for future research further improving the representation of consumers' choice in bottom-up optimization E4 models (see Section 7).

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APPENDIX

Appendix	i
1 Improvements in the representation of behaviour in integrated energy and transport models	iii
2 TIMES-DK: technology-rich multi-sectoral optimisation model of the Danish energy system	xxv
3 Reaching carbon neutral transport sector in Denmark – Evidence from the incorporation of modal shift into the TIMES energy system modeling framework	xlix
4 Improving the representation of modal choice into bottom-up optimization energy system models – The MoCho-TIMES model	lxv
5 Modelling transport modal shift in TIMES models through elasticities of substitution	lxxxv
6 Analyzing effects of transport policies on travelers' behaviour for model shift in Denmark	xcix
7 The cost of electrifying private transport – Evidence from an empirical consumer choice model of Ireland and Denmark	cxxxi
8 A long-term strategy to decarbonise the Danish inland passenger transport sector	cliii
9 The Nordic Electric Vehicle Outlook 2018 - Insights from leaders in electric mobility	clxxiii

**IMPROVEMENTS IN THE
REPRESENTATION OF BEHAVIOUR
IN INTEGRATED ENERGY AND
TRANSPORT MODELS**

Improvements in the representation of behavior in integrated energy and transport models

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ABSTRACT

The inclusion of sociological aspects, as human behavior related to transportation, in energy–economy–environment (E3) models may enable an inclusive representation of the system under analysis, thus providing a more likely representation of reality. This article presents a review of integrated energy and transport models characterized by a detailed description of the passenger transport sector and by the presence of transport behavioral features. First, we propose a working taxonomy based on the level of integration of the energy and transport sectors. As the study underlines, a high level of integration is a precondition for incorporating the consumer behavior related to purchase decisions and use of transport technologies in energy and transport models. Second, we identify and review the recurring behavioral features related to transport included in current integrated energy and transport models: technology choice, modal choice, driving pattern, and new mobility trends. The main contribution of the paper resides in analyzing the modeling methodologies adopted in the literature to incorporate behavioral features in transport and in examining opportunities and challenges of each of them. We draw recommendations on model structure and relevant attributes to consider in relation to consumers' choices in transportation.

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1. Introduction

The dominance of oil use in transport represents a significant obstacle to the transition toward a secure low-carbon energy system: in the past 30 years, global transport energy demand has doubled (IEA, 2014). From 1990 onwards, CO₂ emissions in transport have continued to increase in OECD countries while simultaneously reducing in the industrial and residential sectors, suggesting that current policies to reduce transport demand in OECD countries have been inadequate (IEA, 2009). In addition, transport-related CO₂ emissions in non-OECD countries have doubled over the last 15 years due to the increasing level of car ownership and to the growth of freight transport (IEA, 2015).

There are significant efforts underway in OECD and non-OECD countries to decarbonize transport energy use, with a particular focus on car transport. This includes research and technology development programs by car manufacturers on improving the efficiency of internal combustion engines (ICE), the use of alternative fuels including, but not limited to, compressed natural gas (as a pathway to biomethane), the electrification of transport, and use of hydrogen fuel cell technology. However, technology development is only one of the dimensions to consider in relation to transport CO₂ mitigation: technology adoption and usage are also key factors and point to a need for individual and collective behavioral analysis.

The IEA proposes a combination of both technological and behavioral measures to address transport CO₂ reduction: avoid, shift, and improve (IEA, 2012). *Avoiding* deals with mitigating the mobility demand, either by teleworking, virtual mobility or other demand-management policies. *Shifting* means increasing the market shares of the most efficient and least polluting modes or increasing the use of car sharing and carpooling. *Improving* focuses on pushing the technology performance improvement and in reducing vehicle-specific emissions by decreasing the weight of the vehicle or developing advanced engines.

Energy system models have aided policy-makers in determining optimal policies and least-cost pathways toward CO₂ free energy systems (Knopf et al., 2013; Nakata, Silva, & Rodionov, 2011). Considering the aforementioned measures proposed by the IEA, it could be argued that the acceptance of efficient but more expensive technologies, the systematic shift from private car to public transport, and the option of working from home are not guaranteed occurrences. Previous studies demonstrated the slow pace of decarbonization in the transport sector relative to other sectors over the last decades (Cayla & Maizi, 2015; Cuenot, Fulton, & Staub, 2012; Pietzcker et al., 2014), and highlighted the requirement for both a technological and a behavioral shift (Schäfer, 2012; Waisman, Guivarch, & Lecoq, 2013). Thus, in order for energy system models to continue being a reliable tool for transport mitigation analysis, it is of primary importance

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to incorporate individual and collective decision-making, that is, to represent behavior. This includes accounting of real household preferences and individual attitudes toward the adoption and use of new technologies and services.

It has become increasingly recognized that energy system models are, in general, effective at improving the representation of techno-economic parameters; however, they are poor at capturing the many facets of human behavior (Schäfer, 2012; Waisman et al., 2013). Li, Trutnevyyte, and Strachan (2015) provide a comprehensive framework for socio-technical energy transitions models, and describe techno-economic detail, explicit actor heterogeneity and transition pathway dynamics as fundamental in considering an exhaustive, and thus more complex, representation of the system. Traditional attempts to address human behavior in transport mainly consist of reproducing price response aspects of behavior by means of constant elasticities of substitution and capturing technology adoption via discrete choice models. This paper builds on and adds value to the work of Schäfer (2012) in three ways. First, by reviewing the state of the art in the integration of energy and transport models, second through investigating the modeling methodologies used to incorporate human behavior (related to transport) and identifying the most commonly incorporated behavioral features, and finally by critiquing these methodologies with a focus on modeling framework and assumptions, time and cost for the data collection, and model integration methodology.

The purpose of this review is to assess the methodologies adopted for including aspects of behavior in transport within integrated energy and transport models. The overarching goal is to move beyond a review focusing just on model descriptions, rather to include a degree of analysis and conceptual innovation. Hence, this paper falls into the category of “critical review” (Grant & Booth, 2009) or, equivalently, “issue review” (Noguchi, 2006). Two main research questions guided the work:

- Structure—how should transport and energy models be structured to allow an effective inclusion of behavior?
- Parameterization—what key attributes and parameters should be introduced to represent transport-related consumer choices in an integrated energy and transport model?

The paper is organized as follows. Section 2 illustrates the scope and methodology of the review. Section 3 describes the classification criteria for the models analyzed, specifically considering the level of integration of energy and transport sectors. As means of overcoming the difficulties of model integration, model-linking methodologies are also presented in Section 3. In Section 4, the reviewed models are classified according to the methodology used for introducing the main transport-related behavioral features focusing on technology choice, modal choice, driving pattern, and new mobility trends. Section 5 draws the conclusions by answering the research questions, whereas Section 6 provides an overview

on the policy implications triggered by the advances in transport behavior modeling.

2. Review methodology

The methodology for this critical review comprises three literature filtering and assembling stages. First, we performed an automatic literature search of journal articles and conference proceedings through online academic databases, that is, Web of Science¹ and DTU Findit², to reveal integrated energy and transport modeling tools that include a representation of transport-related behavior. Second, we executed a manual screening to filter for alignment with at least one of the following criteria:

- Analyzing and modeling the integration of sectoral systems into global and partial equilibrium energy–economy–environment (E3) models.
- Incorporating transport-related human behavior in an energy model and describing its impact in enabling a more realistic representation of energy systems.
- Using models to evaluate the policy interventions required to support the transition to efficient and climate-aware behavior in the transport sector.

Third, we integrated the assembled literature with additional sources found through existing reviews addressing integrated energy and transport models (Bhattacharyya & Timilsina, 2010; Connolly, Lund, Mathiesen, & Leahy, 2010; Gargiulo & Gallachóir, 2013; Jebaraj & Iniyar, 2006; Pfenninger, Hawkes, & Keirstead, 2014; Pye & Bataille, 2016; Schäfer, 2012; Yeh et al., 2016).

With respect to the automatic database screening, a first search using the string transport* AND model* AND (behavior\$* OR behaving)³ in the topic field revealed 30,373 hits, which had been progressively reduced to 3846 after excluding not relevant research areas, and to 3200 after excluding not relevant journals and including only works in English language. To filter further the results, the search of the term energy within those previously obtained, provided 331 papers. The manual screening (according to the criteria mentioned above) first by title and then by reading the full papers, yielded, respectively, 29 and 5 relevant studies.

A second search string transport* AND (behavior* OR behaving) AND “energy system” AND model* revealed 24 hits. These have been manually screened to obtain six relevant papers.

As visible from the paper structure, the scope of the analysis becomes progressively more focused throughout the review: it is broader in Section 3 and narrows down in Section 4. Section 3 investigates the state of the art of the integration of energy and transport models, thus requiring also analyzing sectoral models, that is, partial equilibrium

¹<https://www.webofknowledge.com/>

²<https://findit.dtu.dk/>

³For Web of Science search syntax, see http://images.webofknowledge.com/WOKR527R13/help/WOS/hp_search.html

representations of single sectors of the entire economic system. The broader perspective allows a comprehensive view of the features that sectoral-energy and sectoral-transport models are able to capture and the level of detail at which those features can be rendered. In this perspective, we analyze 27 energy and transport models and we propose a model taxonomy founded on the integration of energy and transport systems. In Section 4, we strictly focus on the representation of behavior in integrated energy and transport models, thus limiting the scope to 14 highly integrated energy and transport models.

Within the scope of this review, research focusing on factors influencing behavior and behavioral theories did not constitute part of the analysis. In the same way, the boundaries of our review lie within energy and transport modeling, hence not considering spatial planning, land and water use, and comprehensive environmental assessments, for example, life cycle assessment (LCA). Moreover, we limit our focus to passenger land transport, thus excluding freight, aviation, and maritime transport. Regarding the temporal relevance of the models reviewed, we included the most recent studies (peer-reviewed research published in 2006–2016) for each modeling tool, as well as less recent documents in the case that significant and/or contrasting results were proposed. Although most of the studies analyzed focus on European and American countries, no prior limitations were imposed as per the geographical scope of the review, thus aiming to examine comprehensively the modeling efforts of energy and transport systems worldwide.

3. Classification of integrated energy and transport models

3.1. Integration of energy and transport models

Modeling plays an important role in the analysis of energy and transport systems, creating a simplified version of a complex system, thereby making it an effective tool for decision-making and planning. It is worth noting that energy models do not aspire to predict the exact evolution of the energy system, rather they primarily perform scenario analyses, comparing a number of potential future pathways, which represent a range of possible energy system developments. However, creating models, which are able to capture reality as accurately as possible, is an attempt that should be pursued.

In the field of energy and transport, there are several types of models currently available and in use. Transportation models attempt to capture trends in mobility and help us understand the underlying factors that affect mobility decisions (e.g., Lin, 2015; Rich, Nielsen, Brems, & Hansen, 2010). Transport energy models (e.g., Daly & Ó Gallachóir, 2011; Kloess & Müller, 2011) evaluate future scenarios of transport energy demand and supply, and associated emissions. These tend to be simulation models valuable at assessing the impact of specific policy measures (e.g., Daly & Ó Gallachóir, 2012).

The expected electrification of the transport sector and the likely increase in fuel blends with higher shares of bio-fuels will link the future transport sector even more to the

overall energy system, offering new opportunities and challenges across the supply–demand balance. Therefore, integrated energy system models, as described in the previous reviews by Bhattacharyya and Timilsina (2010) and Gargiulo and Ó Gallachóir (2013), offer a particularly relevant approach following their capability to analyze synergies, interactions and competitions between different energy sectors and with the surrounding economy. These models represent transport energy use within the entire energy system with a specific focus on technology and seek the least-cost energy system pathway to meet future energy service demands (e.g., Juul & Meibom, 2011; Merven, Stone, Hughes, & Cohen, 2012). They are used to undertake climate mitigation scenario analysis, comparing impacts on the energy system (including transport energy system) under a range of emissions reduction constraints and for evaluating energy policies. Integrated assessment models (IAM) also seek a least-cost solution to a particular CO₂ emissions constraint, including transport but generally with a less detailed representation of technology (e.g., Blanford, 2008; Kyle & Kim, 2011).

These model types offer a wide variety of approaches available to researchers and decision-makers within the energy and transport sectors. In accordance with the focus of the analysis, the scope and level of detail required, the role of the analyst is to assess which model is best suited to cope with each specific aspect.

As this review aims at recognizing the minimum level of integration required for suitably incorporating transport behavior in energy models, a taxonomy is hereby proposed for usefully describing the level of integration of the transport sector in the reviewed models.

While acknowledging that there are no strict boundaries between model classes but rather a gradual change, we distinguish five model categories (Table 1): (i) sectoral energy models (E), which consider only the energy-related aspects of the system under analysis; (ii) energy models partially including the transport sector (E+), where the transport sector is represented at an aggregated level; (iii) highly integrated energy and transport system models (E+T), which represent a highly disaggregated level of representation of the transport sector in an energy systems model; (iv) transport models partially including the energy sector (T+), where the energy system is represented at an aggregated level into a model which has a primary focus on transport modeling, and (v) sectoral transport models (T) which are transport models with little or no focus on energy demand and environmental externalities. Table 1 offers a description of the five categories, providing model examples for each. These examples are not necessarily part of the reviewed models, which maintain a closer affinity with the E+T class.

Figure 1 outlines the authors' hypothesis on the importance of moving from sectoral models (E and T) toward more integrated energy and transport models (E+T) to realistically capture the economic, technical, and sociological variables.

Integrated energy and transport models, E+T models, focus on analyzing the potential for the integration of renewable energies in the transport sector (Lund &

Table 1. Taxonomy of energy and transport models.

Category	Description	Focus	Examples
E	<i>Sectoral energy models</i> consider only the energy-related aspects of the system under analysis	Study future projections of energy demand, at different levels of spatial and temporal aggregation	Bottom-up building model (Dineen, Rogan, & Ó Gallachóir, 2015), PLEXOS Gil, Aravena, & Cardenas, 2015)
E+	<i>Energy models partially including the transport sector</i> have an aggregated representation of the transport sector	Take into account the effect of aggregated transport energy demands on the surrounding energy system.	LEAP (Heaps, 2016), Balmorel (Karlsson & Meibom, 2008)
E+T	<i>Highly integrated energy and transport system models</i> contain a highly disaggregated transport sector in an energy system model	Perform transport-focused policy analyses and consider the effects of modal and technology shift on the energy system	ESME (Pye & Daly, 2015), IMACLIM-R (Waisman et al., 2013)
T+	<i>Transport models partially including the energy sector</i> include the energy system at an aggregated level	Analyze the impact of transport technology and modes on energy consumption and emissions or vice versa	MoMo (Fulton, Cazzola, & Cuenot, 2009), ICCT Roadmap (Façanha, Blumberg, & Miller, 2012)
T	<i>Sectoral transport models</i> are transport models with little or no focus on energy demand	Simulate travel trips by origin and destination, trip purpose, mode of travel, and household demographics. Focus traditionally on behavioral aspects of individuals' decisions	LTM (Rich et al., 2010), MA ² T (Lin, 2015)



Figure 1. Representation of the transport sector in our model classes.

Kempton, 2008), assessing the challenges of introducing electric vehicles (EV) (Bahn, Marcy, Vaillancourt, & Waaub, 2013; Bosetti & Longden, 2013; Juul & Meibom, 2011; Kyle & Kim 2011; Seixas et al., 2015), and studying technology and modal shift in the transport sector as a climate mitigation option (McCullum et al., 2017; Pietzcker, Moll, Bauer, & Luderer, 2010; Pye & Daly, 2015). On the other hand, E+, E, T, or T+ models are often applied for specific sectoral policy and scenario analyses. For the purpose and interest of this review, we limit our focus to the models belonging to the category E+T.

3.2. Modeling approach and mathematical method

Energy models are generally classified according to several criteria: van Beek (1999) reviewed different ways of categorizing the models, producing a list of nine classification criteria for energy models. Pandey (2002) and Nakata (2004) provide more recent classifications (see Bhattacharyya & Timilsina, 2010 for further details), whereas Lundqvist and Mattsson (2001) comprehensively examine national transport models.

For the purpose of this work, we classify the energy and transport models analyzed in relation to the modeling approach and mathematical method employed. These two criteria, traditionally adopted for classifying energy models, are here utilized to (i) comprehend the possible methodologies for integrating the transport sector within an energy system model framework and (ii) explore whether a certain approach should be used for describing both the technological and behavioral dimensions.

3.2.1. Mathematical methods: simulation and optimization

According to World Energy Conference (1986), *simulation* models describe the development of a system based on its

logical representation and on exogenously defined assumptions while *optimization* models apply mathematical programming to determine the optimal configuration of the system subject to some constraint(s). Simulation models are referred to as static if they represent the operation of the system in a single period of time, and dynamic if the output of one period affects the output of subsequent periods. Simulation models are effective at showing how future energy demand and supply will evolve according to certain trends of energy drivers, or at reproducing traffic in a road network given certain household characteristics. Concerning transport modeling, these tools can usefully simulate the impact of specific policy measures, as for the model UKTCM (Brand, Tran, & Anable, 2012).

Energy systems models, also referred to as partial equilibrium models, are a particular branch of optimization models that find an equilibrium solution for the energy system alone. This contrasts with general equilibrium models, including computational general equilibrium (CGE) models (Hosoe, Gasawa, & Hashimoto, 2010), where a general equilibrium across the entire economy is achieved. Optimization models are useful for determining potential least-cost solutions to meet a specific policy goal, for instance an emissions reduction target.

3.2.2. Modeling methods: top-down and bottom-up

The second classification criteria considered relates to the level of detail in the description of commodities and technologies of a system, leading to two major classes: *top-down* (TD) models and *bottom-up* (BU) models. The former class of models focuses mainly on the macroeconomic dimensions and aims at capturing the economic influence of prices and markets on the energy and transport sectors using a number of economic variables as drivers for service demands.

The description of the energy and transport system is aggregated and has low technical detail because represented by production functions that reproduce the dynamics of substitution between the different factors (labor, capital, and resources). Two types of models are included in this category: econometric models, focused on short- to medium-term dynamics of adjustment, and CGE models, based on long-term equilibrium after adjustments, for example, the EPPA model by Karplus, Paltsev, Babiker, and Reilly (2013). The TD modeling approach can be effective at providing technology roadmaps but lack the level of detail required to determine the individual policy measures to meet these results.

BU modeling seeks to provide a more technologically rich representation of demand and supply. These can be (either single or multi-sectoral) simulation models (e.g., Daly & Ó Gallachóir, 2011) or full-energy systems optimization models, for example, MARKAL (Loulou, Goldstein, & Noble, 2004) and MESSAGE (McCollum, Krey, Kolp, Nagai, & Riahi, 2014). Within BU models, existing or under development technologies are carefully characterized along the entire supply chain by means of technical, economic, and environmental parameters. The energy system is then represented as a network of technologies and commodities, called reference energy system (RES). BU energy models are commonly partial equilibrium models, that is, they consider only one aspect of the energy system. The macroeconomic background remains vaguely defined and the relationship between the energy and the outside sectors with the rest of the economy is simplified. This results in a high level of detail surrounding one sector but fails to give the same foresight of the complete economy as TD models.

TD and BU modeling approaches complement each other: the aspects where TD models reveal weaknesses are often those where BU is stronger. Therefore, efforts have been put in creating the so-called *hybrid* models (Hourcade, Jaccard, Bataille, & Gheris, 2010). Such modeling approach can be either based on increasing the technological detail of conventional TD models (as, e.g., in the models WITCH (Bosetti, Tavoni, De Cian, & Sgobbi, 2009), ReMIND (Pietzcker et al., 2010), and IMACLIM-R (Waisman et al., 2013)), or on including a more detailed representation of the macroeconomic background in BU models (cf. e.g., the models CIMS (Horne, Jaccard, & Tiedemann, 2005) and GCAM (Kyle & Kim 2011)). Some models are more difficult to classify but are most readily also grouped in the hybrid category, including some integrated assessment models (e.g., the model MERGE (Blanford, 2008)) and other types of hybrid models (e.g., the model PRIMES (E3MLab, 2014)).

3.3. Discussion on energy and transport models integration

A classification of the reviewed integrated energy and transport models (E+T), according to geographic scope, time horizon, mathematical method, and modeling approach, is presented in Table 2. Focus denotes the specific problem dealt within the cited reference.

The vast majority of the studies are used for long-term analyses with a time horizon of 50–100 years, as evident from Table 2. This observation is in line with the fact that energy and transport models are often developed to assess optimal long-term pathways toward a certain environmental goal and to inform decision-makers early in advance on policies and measures which can be efficient and effective in the long run. On the other hand, sectoral transport models T often focus on traffic assignment in a shorter run, due to, for example, the underlying uncertainties on the future development of the road infrastructure.

As regards the geographical scope, 12 out of the 27 studies reviewed have a country scope, 10 have a global outlook, three are developed at regional level, and one at city level. However, many of these models are adaptable to different geographical contexts (see the open-source energy system model OSeMOSYS (Howells et al., 2011)) and can be applied to perform comparative studies for different countries (Mittal, Dai, & Shukla, 2016; Zhang, Chen, & Huang, 2016). Some of the models (e.g., PRIMES-TREMOVE (E3MLab, 2014), TRAVEL (Girod, van Vuuren, & Deetman, 2012), and UKTCM (Brand et al., 2012)) are detailed representations of the transport sector, which can be linked or integrated within a wider energy system model. In this latter case, mathematical method and modeling approach refer to the more detailed transport module.

Figure 2 reports the cross classification for the 27 reviewed studies, according to modeling approach and mathematical method. The majority of the E+T models considered falls in the category of optimization models (16) while amongst the remaining, 8 are simulation models and 3 are CGE. Among optimization models, the majority are BU models (14) while 2 belong to the hybrid type. Once more, the TD approach is traditionally used in macroeconomic models, where the energy and transport systems appear at a more aggregated level. Hence, an E+T model with a detailed representation of the transport system is often not possible or not pursued.

Transport models T and T+, focusing on the factors that affect mobility decisions, are mainly based on a simulation method. On the other hand, the review highlights that most of the E+T models adopt an optimization method. Therefore, when the aim is to incorporate transport behavioral features in energy models, the challenge of combining a simulation approach within a traditional optimization model structure needs to be taken into account. For instance, the structure of the nested multinomial logit model MA³T (Lin, 2015; Lin & Greene, 2010) is replicated in the optimization model COCHIN-TIMES (Bunch, Ramea, Yeh, & Yang, 2015).

Six out of the 27 reviewed references are hybrid models, which combine the top-down with the bottom-up approach. As we will further highlight in Section 4, hybrid models better allow introducing a detailed modeling of technological, macroeconomic, and microeconomic characteristics of the energy system. Nevertheless, modeling and computational difficulties may arise when introducing several parameters and constraints in one single model framework. Therefore, most attention has been set on integrating the various

Table 2. Classification of integrated energy and transport models.

Model name	Geographic scope	Time horizon	Mathematical method	Modeling approach	Focus	Reference
AIM/End-use Balmorl	China, India Nordic and Baltic countries	2010–2050 Year 2030 with hourly resolution	O O	BU BU	Comparison of low-carbon urban transport scenarios for China and India Creation of a road transport add-on to traditional Balmorl model, to assess integrated power and transport systems and vehicle to grid and emissions	Mittal et al. (2016) Juul and Meibom (2011)
BLUE	United Kingdom	2010–2050	S	H	Dynamic stochastic simulation of technology diffusion, energy and emissions	Li and Strachan (2017)
CIMS	Canada	2005–2035	S	H	Modeling technological changes in a more behaviorally realistic manner to facilitate policy analysis for a greater range of technologies	Horne et al. (2005)
COCHIN-TIMES	California	2005–2050	O	BU	Demonstration of a practical approach for incorporating behavioral effects from vehicle choice models into E4 models	Bunch et al. (2015)
ECLIPSE	Global	2000–2100	CGE	H	Development of an integrated energy-economy model with a detailed transport sector representation	Turton (2008)
EnergyPLAN	Denmark	Year 2020 with hourly resolution	S	BU	Integration of renewable energy into the transport and electricity sectors through vehicle-to-grid technology	Lund and Kempton (2008)
EPPA	Global	2005–2050	CGE	TD	Disaggregation of the passenger vehicle transport sector in a CGE model	Karplus et al. (2013)
ESME	United Kingdom	2010–2050	O	BU	Representation of endogenous mode shift for urban passenger travel in a whole energy system model	Pye and Daly (2015)
EXSS	Ahmedabad, India	2015–2035	S	BU	Analysis of co-benefits of low-carbon passenger transport actions in an Indian city	Pathak and Shukla (2016)
GCAM	Global	2005–2095	S	BU	Long-term effect of alternative vehicles on greenhouse gas emissions and energy demand	Kyle and Kim (2011), Mishra et al. (2013)
GET-R	Global	2010–2100	O	BU	Analysis of fuel and vehicle technology choice for passenger transport under CO ₂ targets	Grahn, Kämpf, Whalen, and Wallington (2013)
IMACLIM-R	Global	2001–2100	CGE	H	Implications of modeling non-price determinants of mobility	Waisman et al. 2013
Irish TIMES	Ireland, California	2005–2050	O	BU	Incorporating modal choice within passenger transport in a TIMES model	Daly et al. (2014)
MESSAGE	Global	2005–2100	O	BU	Introduction of consumers' heterogeneity and non-monetary parameters	McCollum et al. (2017)
OPUS	User-dependent	User-dependent	O	BU	Description of the open-source energy system model	Powells et al. (2011)
PETAS	Europe	2005–2050	O	BU	Advanced transport module for scenario and policy analysis of the European transport sector, stand-alone or fully linked with PRIMES energy model	Estrella et al. (2015) ESMLabs (2014)
PRIMES-TREMOVE	Europe	2005–2050	S	BU	European transport sector, stand-alone or fully linked with PRIMES energy model	
ReMIND	Global	2005–2100	O	H	Analysis of technology and mode shift as different mitigation options for the transport sector	Pietzcker et al. (2010)
SATIM	South Africa	2006–2050	O	BU	Describing the TIMES model of the entire energy system in South Africa	Merven et al. (2012)
TIAM-UCL	Global	2010–2100	O	BU	Explore the competitive and/or complementary relationship between hydrogen and electricity, with endogenous technological learning	Anandajah and McDowall (2015)
TIMES California	California	2005–2050	O	BU	Assess least-cost mitigation options required to meet California's long-term 80% greenhouse gas emission reduction goal, by considering all the energy sectors	McCollum, Yang, Yeh, and Ogden (2012)
TIMES Canada	Canada	2007–2050	O	BU	Perform policy analysis for promoting electrification of road transport in Canada	Bahn et al. (2013)
TRAVEL	Global	2010–2100	S	BU	Predict global travel demand, modal split shifts, and changes in technology and energy use	Girod et al. (2012)
UKTCM	United Kingdom	2010–2050	S	BU	Policy analyses and low-carbon strategy development for the transport sector	Brond et al. (2012)
US-TIMES	USA	2010–2050	O	BU	Comparison of transport scenarios between China and US, with focus on technological shift	Zhang et al. (2016)
WITCH	Global	2005–2100	O	H	Review of the electrification of light duty vehicles within a model that utilizes a learning-by-researching structure	Bosetti and Longden (2013)

S: simulation; O: optimization; CGE: computable general equilibrium; BU: bottom-up; TD: top-down; H: hybrid.

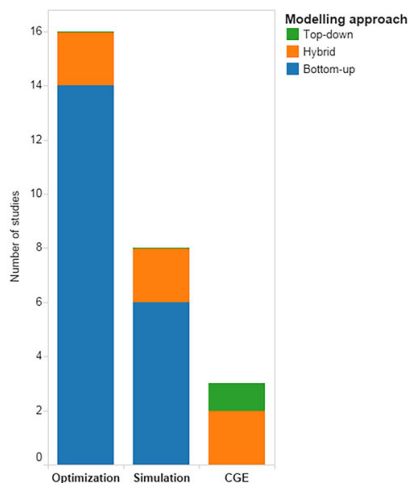


Figure 2. Mathematical method and modeling approach of the reviewed E + T models.

approaches through model linking, with the aim to harness the richness of each model type through the creation of an interaction. Section 3.4 provides a comprehensive review of the model-linking techniques used between energy models with a focus on the linkage between energy and transport models. However, very few cases to date have considered a coupling of these two forms. Therefore, this review considers the linking methodology between an array of energy models, regardless of the sector, highlighting the advantages and disadvantages of the different techniques, and provides case studies addressing transport modeling where applicable.

3.4. Model-linking methods

Combining different modeling approaches can take advantage of the strengths of individual methodologies and add value and insight to individual approaches. Model coupling methodologies can be classed by means of operation (as done by Labriet et al., 2015 and Bohringer & Rutherford, 2009). This paper splits these methodologies into three classes: (i) Independent Model Convergence, (ii) Partial Integration, and (iii) Full Integration. Model-linking methods can be used as a means of improving the representation of behavior into a model which previously neglects this area, with examples found below. A definition of each class follows, with a detailed focus on soft linking between energy and transport models.

3.4.1. Independent model convergence (IMC)

Under IMC operation, two models are run independently of each other and done so until a convergence is reached. This

methodology requires the least level of structuring of the models among the three classes and has been identified as a faster and more versatile procedure than a fully integrated model; however, it is much more susceptible to errors arising due to inconsistencies between models. Mulholland, Rogan, and Ó Gallachóir (2015) carried out this approach between a sectoral simulation model of the private car fleet and the Irish TIMES energy system optimization model to determine the magnitude of the policy measures which would be required on an annual basis for this sector to contribute to an overall 80% CO₂ reduction by 2050, relative to 1990. The study concluded that the time resolution of survival profiles on the private car sector in the Irish TIMES model was overly optimistic and thereby corrected using results from the private car stock simulation model. These two models operate on different principles (simulation vs. optimization) and linkage between the two will still result in fundamental errors but allows for a versatile model operation. Daly, Gargiulo, and Ó Gallachóir (2011) carried out a similar approach, considering a soft-link between these two models with a more specific focus on the underlying modeling principles and projections of energy service demand.

3.4.2. Partial integration (PI)

PI involves the integration of some detail from the bottom-up model into the top-down model, or vice versa, to create a scaled-down representation of one model in the second. By far, the most common approach is the integration of bottom-up data into a top-down model, generally to improve sectoral representation into a CGE model, which is the case in Schäfer and Jacoby (2005) who carry out this methodology with a specific focus on the transport sector. In this study, a modal shift model and a MARKAL model of household and industry transport activities (bottom-up) are integrated into a CGE model (top-down) to provide an analysis on the penetration of new automobile technologies. This method found an inconsistency between energy use with bottom-up and top-down models due to errors in calibration although Kiulla and Rutherford (2013) address this inconsistency by providing an “as best as possible” match between models. Similarly, Merven et al. (2012) soft-linked five models to create long-term projections of the transport sector in South Africa. This consisted in developing and linking a CGE model, a vehicle Parc model, a time-budget model, a freight demand model, and a fuel demand model. The outputs from the CGE model (i.e., GDP levels) were used to provide the baseline scenarios for the vehicle park and freight demand models, while the fuel demand and time-budget models improved the representation of behavior used in long-term projections.

3.4.3. Full integration (FI)

The least common of all coupling methods, FI operation is carried out by a complete integration of both models, requiring both models to be built within the same mathematical format. This combats the inconsistencies between top-down and bottom-up modeling techniques, yet requires increased

processing power. To the best of the authors' knowledge, this method has never been carried out in modeling of the transport sector although a few examples are found using other sectors. A pedagogic analysis is carried out in Bohringer and Rutherford (2008) which praises the coherence of this integration, but identifies the limitations associated with dimensionality between models. A second approach is considered in Bohringer and Rutherford (2009) which decomposes the integrated mixed complementarity problem (MCP) formulation to successfully address the problem with dimensionality. Lanz and Rausch (2011) employ this decomposition method in modeling US climate policy. This method of model linkage is also known as "hard-linking" while the previous two methods are "soft-linking" methods.

4. Transport behavior in energy and transport models

Although energy system models are capable of acting as effective decision-making tools by providing valuable insights into the dynamics of the different energy sectors, they may not always be fully comprehensive. Jaccard, Nyboer, Bataille, and Sadownik (2003) accurately described the level of comprehension in an energy system model:

An ideal energy system model should include technological explicitness, microeconomic realism and macroeconomic completeness.

Technological explicitness refers to the quality of including a vast amount of information about the performance of technologies. *Microeconomic realism* relates to a realistic representation of consumer behavior when dealing with decision-making. This requires the model to be able to include not only the description of economic parameters but also of other attributes related to the level of service and sociological aspects. *Macroeconomic completeness* consists of taking into account the feedback of the dynamics and transformations occurring in the energy system on the rest of the economic sectors.

Although a holistic analysis should comprehend all three of these dimensions, the majority of energy models fail to do so. As illustrated in Section 3, model-linking and hybrid models currently represent the only approaches for merging these three characteristics in a single modeling framework.

This section explores the dimension of *microeconomic realism* proceeded by examples to date, specifically addressing consumer behavior related to purchase decisions and use of transport technologies.

Schäfer (2012) reviews and identifies the lack of behavior representation in energy models, suggesting the inclusion of five main features to simulate behavioral change in transportation: elastic transportation demand, endogenous mode choice, choice of no physical travel, infrastructure capacity representation, and segmentation of urban and intercity transport. His study indicates that a considerable investment in research and development is required for a breakthrough in the specifics of new technologies for achieving CO₂ reduction. At the same time, the behavioral dimension is also

fundamental: new technologies have to be accepted by people and therefore it is important to include a description of the real household preferences, their behavior when taking decisions, and their acceptance of different transport technologies in energy models. Furthermore, empirical results show a link between lifestyle and sustainability in travel behavior, calling for a paradigmatic shift in transportation policy from capacity/demand management toward lifestyle adjustments (Fan & Khattak, 2012).

Consumer choice is generally not accurately represented in energy models: either the transport market shares are endogenously determined accounting only for the life cycle costs of the different alternatives, or they are exogenous inputs deriving from the assumed consequence of some energy policy, such as in Bahn et al. (2013). In this second case, Bunch et al. (2015) illustrate that there is a gap between the real consumers' preferences and the assumed market shares in the scenarios.

As a response to the limitation of the energy system models highlighted in Schäfer (2012), there has been a recent trend in attempting to integrate behavioral transport models within larger E3 models (Waisman et al., 2013). Instead of performing traditional "what if" scenario analysis, the research interest has shifted to the endogenization of modal and vehicle choice in a behaviorally realistic manner (Bunch et al., 2015; Daly et al., 2014). Such approaches require both modal and vehicle shares to be selected not only according to a cost optimization but also including other factors, for example, travel time and infrastructure availability. As an additional trait of behavioral realism, the representation of population heterogeneity is increasingly represented in E+T models. A much more realistic result is achieved when the consumers are disaggregated by classes according to their access to technology, their level of demand and their income, as demonstrated by Cayla and Maïzi (2015) for the residential and transport sector.

The purpose of this section is to review the most remarkable features incorporated in energy and transport models (E+T) to represent transport behavior. From the 27 models reviewed in Section 3, 14 studies have been further analyzed, as these include some of the transport behavioral aspects identified.

4.1. Behavioral features

The recurring ways to include behavior in energy and transport systems have been classified in the four categories: (i) Technology choice, (ii) Modal choice, (iii) Driving pattern, and (iv) New mobility trends.

The rationale behind the selection of these features departs from the works by Schäfer (2012), Li et al. (2015), and McCollum et al. (2017), examining the recurring applications related to behavior introduction in current energy and transport models, and identifying new and complementary attributes.

- i. *Technology choice* represents the possibility for the model to endogenously select a particular transport

technology from a set, based on cost and non-cost parameters. More specifically, to represent consumers' behavior, non-monetary factors are commonly utilized. The concept of technology choice is typically applied to choice of road vehicles.

- ii. *Modal choice* represents the option for the model to determine endogenously the market shares of the different transport modes. This represents a powerful feature when studying the potential for future modal shift to more sustainable transport modes, such as the shift from private car to public transport or even to non-motorized modes.
- iii. *Driving pattern* is generally defined as the speed profile of the vehicle, but can be expanded to include other aspects of driving behavior, such as eco-driving (Ericsson, 2001), or simply distance traveled in a certain period.
- iv. *New mobility trends* include recent developments in the use of transport systems, fostered by the introduction of different services and Information and Communication Technology (ICT) applications. Advancements in this area allow consumers to better manage their trips including phenomena such as intelligent transport systems, car sharing, carpooling, trip chaining, autonomous vehicles, mobility as a service (MaaS), and optional transport abdication.

As discussed further on, *modal choice* and *technology choice* are more commonly included than the other categories. However, analyses show that the potential emission reduction achievable by promoting car sharing and carpooling is high. In fact, by increasing the occupancy factor of light-duty personal vehicles from the current value for Denmark of 1.55 person/vehicle and for Ireland of 1.49 person/vehicle to a desirable value of 2 person/vehicle⁴, the reduction in overall CO₂ emissions for the transport sector would be 15% in Denmark and 25% in Ireland as a yearly average over the period 2015–2050⁵. Such a significant potential constitutes the rationale for including *new mobility trends* among the transport behavior aspects considered in the review. Moreover, modeling *driving patterns* can improve the representation of the road transport sector and its influence on the whole energy system, since driving pattern affects the emission and fuel use of vehicles.

4.2. Discussion on behavioral features representation

The four behavioral features identified in the 14 E + T models reviewed are presented in Table 3 while advantages and disadvantages of the various methodologies are discussed in the remainder of this section. As summarized in Figure 3, 12

of the 14 models reviewed include a representation of modal choice, 9 represent technology choice, 5 of them model driving pattern, and only one is dealing with new mobility trends. The analysis will underline the reason behind the easier applicability of concepts as technology choice and modal choice with respect to fewer implementations of driving pattern and new mobility trends. Among the reviewed studies, hybrid models have the potential to capture all of the four behavioral features although the scope of the analysis will determine the appropriate level of detail for each characteristic. Hybrid models, as, for example, CIMS (Horne et al., 2005), IMACLIM-R (Waisman et al., 2013), and ReMIND (Pietzcker et al., 2010), specifically build a framework able to investigate trends across different systems or knowledge domains. Therefore, they are inherently meant for carrying out cross-disciplinary analyses and give answers to research and policy questions from a broader perspective. To limit model complexity, these gains could come at the expense of a more aggregated representation of reality. On the other hand, bottom-up and top-down models often address a specific energy and transport policy issue, for example, as for EPPA (Karplus et al., 2013), ESME (Pye & Daly, 2015), and UKTCM (Brand et al., 2012). In this case, models can provide robust insights on a certain phenomenon, as the future potential for modal shift (Girod et al., 2012) or the acceptance and penetration of electric vehicles in the transport sector (Bunch et al., 2015).

4.2.1. Technology choice

Energy system models are usually technology-rich, thus allowing a precise description of the technical, environmental, and economic characteristics of the technologies taken into consideration. Nonetheless, in determining the optimal shares to fulfill the travel service demand, traditionally these models only regard the life cycle costs of the technology (actualized investment, operation and maintenance, and fuel costs), disregarding that vehicle preferences are highly heterogeneous and based on many non-economic aspects. McCollum et al. (2017), recognizing that low-carbon future transport scenarios have been explored so far without adequately considering any behavioral aspect, have recently addressed the topic of behavioral realism of vehicle choice in IAM. We identified four main methodologies that are generally used to represent technology choice in a more behaviorally realistic way: (i) discrete choice models, (ii) constant elasticities of substitution, (iii) disutility costs, and (iv) hurdle rates. Additionally, we review the technique of modeling virtual technologies (v) as a means of representing technology choice. While the latter methodology focuses on the residential sector, this approach may be extended to the transport sector. A common trait of all these approaches is that they attempt to capture consumer behavior when choosing a transport technology by including some non-monetary parameters that affect a consumer's decisions.

4.2.1.1. Discrete choice models. The most common approach observed in the literature to introduce technology choice is through discrete choice models. In our review, five

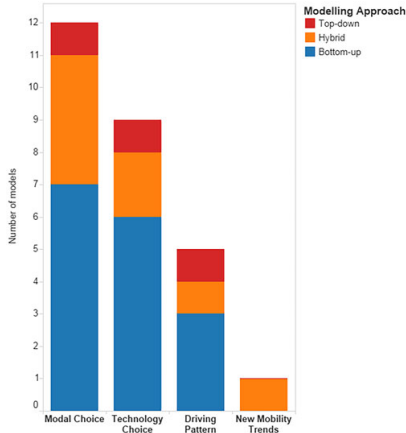
⁴The European Environment Agency showed that values close to 2 for car occupancy have been reached in some European countries in 2008. Hence, the value has been chosen to represent carpooling as an important phenomenon in the two countries.

⁵The analysis has been performed with the bottom-up optimization energy model TIMES-DK for the period 2015–2050 for Denmark, and with the bottom-up sectoral simulation model CarSTOCK for Ireland.

Table 3. Representation of transport behavioral features in energy and transport models.

Model name	Technology choice	Modal choice	Driving pattern	New mobility trends	Modeling approach	Reference
BLUE	Intangible costs/benefits, Hurdle rates	–	–	–	H	Li and Strachan (2017)
CIMS	MNL	MNL	–	MNL	H	Horne et al. (2005)
COCHIN-TIMES	Disutility costs	–	Driving profiles	–	BU	Bunch et al. (2015)
ECLIPSE	–	TTB	–	–	H	Turton (2008)
EPPA	Nested CES	Nested CES	E	–	TD	Karplus et al. (2013)
ESME	–	TTB	–	–	BU	Pye and Daly (2015)
GCAM	NMNL	LM	–	–	BU	Kyle and Kim (2011), Mishra et al. (2013)
IMACLIM-R	–	TTB, CES	E	–	H	Waisman et al. (2013)
Irish TIMES, CA-TIMES	–	TTB, TTI	–	–	BU	Daly et al. (2014)
MESSAGE-TRANSPORT	Disutility costs	MNL	Driving profiles	–	BU	McCollum et al. (2017)
PRIMES-TREMOVE	NMNL	CES	Driving profiles	–	BU	E3MLab (2014)
ReMIND	–	Nested CES	–	–	H	Pietzcker et al. (2010)
TRAVEL	NMNL	NMNL	–	–	BU	Girod et al. (2012)
UKTCM	LM	E	–	–	BU	Brand et al. (2012)

NMNL: nested multinomial logit model; MNL: multinomial logit model; LM: logit model; TTB: Standard budget and time budget constraints; TTI: travel time investment; E: elasticities; CES: constant elasticities of substitution.

**Figure 3.** Distribution of the modeling approaches across the four behavioral features.

models have been found to use this methodology, as shown in Table 3.

Discrete choice models calculate the probability of an individual's choice from a finite set of alternatives. The selection of an alternative is determined through the principle of random utility maximization, which assumes that individuals aim at maximizing their utility when making a choice. Each alternative is characterized by means of both monetary and non-monetary parameters that influence people's choice.

As an example, Equation (1) illustrates the standard formula for a multinomial logit model (MNL)—a form of discrete choice modeling, which is used in the global transport model TRAVEL (Girod et al., 2012). This model calculates passenger transport shares and it is part of the energy model TIMER, which is in turn included in the wider IAM framework IMAGE (van Sluisveld, Martínez, Daioglou, & van Vuuren, 2016). Equation (1) calculates the fleet composition

within a travel mode m at each time period t and region r for each vehicle v . The share of each alternative is calculated by comparing its cost with that of all the competing technologies within an exponential function that uses λ as a calibration factor.

$$Share_{r,v,t} = \frac{e^{(\lambda \times Cost_{r,v,t})}}{\sum_i e^{(\lambda \times Cost_{r,v,t})}} \quad (1)$$

In TRAVEL, the cost characterizing each technology is calculated as shown in Equation (2).

$$Cost_{r,v,t} = \frac{AddTechCosts_{v,t} + EnergyCosts_{r,v,t} + NonEnergyCosts_{r,t}}{load_{r,t}} \quad (2)$$

The total cost is the sum of three addends:

- Investment into vehicles ($AddTechCosts_{v,t}$)
- Energy costs accounting for vehicle efficiency and energy prices ($EnergyCosts_{r,v,t}$)
- Non-energy costs related to vehicle purchase and maintenance, which simulate the increased willingness to pay, associated with higher levels of income ($NonEnergyCosts_{r,t}$)

In the hybrid model CIMS (Horne et al., 2005), an MNL model for vehicle choice is developed from stated preference surveys where respondents are asked to choose among four vehicle types defined by attributes such as capital costs, operating costs, fuel availability, express lane access, emissions, and power. The gathered data serve to build the utility functions for each vehicle type j , as visible from Equation (3):

$$U_j = \vec{\beta}_j^* \vec{X}_j + ASC_j \quad (3)$$

The vector of attributes \vec{X}_j is multiplied by the weighting coefficient vector $\vec{\beta}_j$, with the variable Alternative Substitution Constant ASC representing a specific constant for the alternative technology j . To represent this function in CIMS, market shares are computed according to Equation (4),

where the utility functions are translated into capital costs (CC_j), operating costs (OC_j), and non-financial costs (travel time and comfort) per each mode i_j with a private discount rate r , and market heterogeneity exponent v :

$$Share_j = \frac{e^{U_j}}{\sum_j e^{U_j}} = \frac{\left[CC_j \times \frac{r}{1-(1+r)^{-n}} + OC_j + i_j \right]^{-v}}{\sum_j \left[CC_j \times \frac{r}{1-(1+r)^{-n}} + OC_j + i_j \right]^{-v}} \quad (4)$$

As demonstrated by the two examples reported above, discrete choice models are effective for introducing non-monetary parameters that affect individual's decisions. Among the most commonly used intangible costs included in such models are technical risk of immature technologies, model availability, acceptance factors (to simulate accelerated market diffusion), density of recharging/refueling infrastructure, and range limitations.

Normally, the estimation of the model parameters and the calibration require data from a survey and a statistical analysis of the surveyed data. The time and cost of the data collection are a function of the number of alternatives to be included in the model. Discrete choice models find large-scale application in simulation programs, where parameters statistically inferred from the survey simulate consumer behavior. Conversely, optimization models are often based on linear programming methods; hence, model linking or a linearization procedure is required for the integration of the discrete choice models.

4.2.1.2. Constant elasticities of substitution. Another method of representing transport technology choice in the literature is that of using constant elasticities of substitution (CES). The CES between two input parameters of a utility function measure the constant percentage response of the relative marginal product of the two parameters to a percentage change of the proportion of the parameters.

In the CGE model EPPA (Karplus et al., 2013), the original nesting structure described in Paltsev, Viguier, Babiker, Reilly, and Tay (2004) has been extended to include the possibility of substitution between conventional internal combustion engine vehicles (ICE) and alternative fuelled vehicles (AFV), as shown in Figure 4.

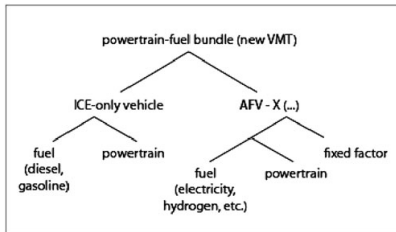


Figure 4. Representation of passenger vehicle choice in EPPA (Karplus et al., 2013).

CES regulate the choice between the transport categories, based on fuel costs, powertrain costs, and a fixed factor, the latter accounting for different constraints on the adoption of alternative vehicles. Constraints on adoption include the gradual fleet turnover, dynamic changes in the relative cost of alternative technologies with respect to the existing technology, and fixed costs associated with reaching a stable production and obtaining wide market acceptance.

The main advantage of CES is that capturing consumer behavior in technology choice only requires the inclusion of additional input factors to capital and labor in the standard production functions. One problem associated with this method is that CES are generally the result of an educated guess or a literature review since they cannot be calculated empirically. Moreover, they typically find application in top-down macroeconomic models and thus the integration in conventional energy models requires the adoption of soft linking or the use of a hybrid modeling approach.

4.2.1.3. Disutility costs. The incorporation of disutility costs allows for considering the (often non-monetary) discomfort costs encountered by consumers when adopting a specific transport technology. Electric vehicles (EV) offer a common example, wherein the users could associate EVs with lack of refueling infrastructure, range anxiety, and scarce vehicle model variety.

McCollum et al. (2014) provide a first example of the use of disutility costs in a linear programming model. In this case, technology choice is limited to fuel choice, including inconvenience costs for non-liquid fuels. A much more extensive use of disutility costs is offered by COCHIN-TIMES (Bunch et al., 2015) and MESSAGE-TRANSPORT (McCollum et al., 2017). The two studies apply the same methodology in different model frameworks: a linear programming tool (TIMES/MESSAGE) has been transformed to be able to replicate the output of MA³T, an MNL model designed to estimate the choice probabilities of an array of technologies for different consumer groups (Lin, 2015; Lin & Greene, 2010). By adding some extra features such as heterogeneity of population, disutility terms, and calibration parameters, the optimization framework is used as a “simulation-like” model. Heterogeneity is introduced to overcome the traditional concept of “mean representative decision-agent” (McCollum et al., 2017) and to take into account that distinct consumer groups are characterized by different preferences toward vehicle adoption and operation. In Bunch et al. (2015) and McCollum et al. (2017), consumers are differentiated along several dimensions: settlement pattern (urban, suburban, and rural), attitude toward technology adoption (early adopter, early majority, and late majority), and vehicle usage intensity (modest driver, average driver, and frequent driver). Then, disutility costs are included to reflect that the different classes of transport users have varying preferences and comfort perceptions toward refueling and recharging station accessibility, range anxiety, and model availability.

While in MESSAGE-TRANSPORT disutility costs are homogeneous within each consumer group, the “unobserved

consumer heterogeneity” is represented through distribution functions (called “clones”) in COCHIN-TIMES (Bunch et al., 2015), thus bringing the model closer to the simulation model MA³T. This approach allows overcoming sharp technology penetration. However, the modeling complexity grows significantly, requiring high-level computational capacity.

Acknowledging that actors have varying sensitivities to cost differentials when making investment decisions, Li and Strachan (2017) include market heterogeneity and intangible costs/benefits in the dynamic stochastic socio-technical simulation model BLUE.

The authors recognize the combination of transport users’ heterogeneity and disutility costs as the most advanced and effective way to improve the behavioral realism of vehicle choice in optimization models.

4.2.1.4. Hurdle rates. Hurdle rates are higher discount factors associated with new or not fully commercial technologies. Hurdle rates account for the higher investment risk, uncertainty, and imperfect knowledge perceived by the consumer, thus simulating the hesitancy to invest in a newer technology over an established technology (Mallah & Bansal, 2011).

With respect to the transport system, the application of higher discount rates on less mature, more uncertain technologies is a traditional method to model vehicle choice. A simple approach consists in having technology-specific hurdle rates while a more sophisticated method considers consumer-specific rates.

In the model BLUE, Li and Strachan (2017) associate different hurdle rates to reflect actors’ different attitudes toward investment risk. Horne et al. (2015) explicitly include the variable discount rate as part of the multinomial logit formulation within the model CIMS, to simulate people’s varying behavior in vehicle purchasing decisions. The UKTCM model (Brand et al., 2012) distinguishes three main market segments for cars: private, fleet, and business car buyers. Higher hurdle rates are associated with private vehicles to emphasize the higher total upfront costs confronted by the private consumer with respect to the fleet or business buyer.

The allocation of variable hurdle rates to technology and consumer groups is a simple and generally applicable methodology in energy and transport models. The difficult calibration procedure and sole reliance on literature values for the determination of the discount rates represent a limitation for this approach.

4.2.1.5. Virtual technologies. Fragnière, Kanala, Moresino, Reveiu, and Smeureanu (2017) and Kanala, Turin, and Fragnière (2013) present a potential methodology to directly introduce technology choice in the bottom-up optimization framework MARKAL. Sociological surveys are conducted to collect data on the willingness to change behavior toward lighting technologies (from existing incandescent bulbs toward new low-consumption bulbs). The underlying assumption is that people are influenced by marketing/awareness campaigns, level of education, quality of

information received, and training. Subsequently, through survey analysis, people are grouped based on their choices and Virtual Technologies are introduced in the MARKAL model to simulate energy savings and technology switch. The introduction of these Virtual Technologies ensures that existing and new technologies compete not only on economic parameters. Efficiency and investment cost are specified for the Virtual Technologies, reflecting the estimated efficiency and investment cost of the marketing campaigns.

Although the method has been applied to the residential sector, it could be effectively extended to the transport sector. Moreover, this approach is easily applicable in bottom-up optimization models since it does not require any deep modification to the model structure. On the other side, the time and cost for survey data collection could be an obstacle to the implementation. Additionally, surveys are often relying on stated preferences (SP) and not revealed preferences (RP). The principal critique is that an individual’s stated preferences may not correspond closely to their actual preferences—the cause of divergence being bias in SP responses or difficulty in carrying out the SP task (Wardman, 1988).

4.2.2. Modal choice

Transport simulation models such as LTM (Rich et al., 2010) have traditionally addressed modal choice using a four-step model structure, including trip generation, trip distribution, mode choice, and route assignment. In the third step, modal shares are normally computed via MNL or NMNL models using a large number of attributes describing the level of service of the alternative modes and the socioeconomic composition of the population. Such an approach has some limitations: first, the need to conduct travel surveys to calibrate the model parameters (normally by means of log likelihood estimation). Moreover, the methodology is limited to simulation models, being the logit model structure based on exponential functions that cannot be implemented in the linear optimization models commonly used for energy system analysis.

The endogenous incorporation of modal choice allows energy system models to determine the optimal pathway toward a policy target as a combination of technological and fuel switching, efficiency improvement, and modal shifting, without relying on external assumptions on modal shares.

Modal choice proves to be a relevant behavioral feature to be included in E+T models, being present in 12 out of the 14 models analyzed. One of the main variables driving modal choice is travel time. Thus, an ongoing tendency to emphasize time importance in mode selection is that of including a constraint on the total travel time of the system: four of the models reviewed set a limit to the overall travel time within the linear optimization program. The main approaches identified for the representation of modal choice are as follows: (i) Travel Time Budget (TTB), (ii) discrete choice models, and (iii) constant elasticities of substitution.

4.2.2.1. Travel time budget (TTB). The rationale behind the adoption of the concept of travel time budget (TTB) has been provided by Schäfer and Victor (2000), who claim that

across different societies, geographical areas, and income classes, people spend the same amount of hours per day traveling. Ahmed and Stopher (2014) provide an updated review of TTB studies, reporting a universal range for the TTB, equal to 60–90 minutes per person per day.

Models including the concept of TTB require changing the model structure to incorporate a new parameter, that is, speed. Speed is specified for every mode, eventually for every trip distance, and, within the optimization program, an upper bound on time consumption is set equal to the TTB.

Daly et al. (2014) apply the TTB concept to the TIMES models of Ireland and of California. This study aggregates all the mode-specific travel demands into a few “trans-modal” demand segments to allow a shift between modes, and subsequently uses a TTB to enable competition between fast but expensive technologies and cheap but slow technologies. With such modeling approach, the optimal solution is not just the one that minimizes total system cost, but it also guarantees that the total system travel time does not exceed the TTB. The approach based on the TTB can be complemented by the concept of travel time investment (TTI), a proxy variable simulating the relationship between modal speed and infrastructure investment. Once TTI is incorporated in the model, it is possible to assess the influence of investing in the infrastructure of a certain mode on the market share of that mode. For instance, in Daly et al. (2014), TTI is used so that the model can invest endogenously in the infrastructure of modes, hence increasing their speed and reducing the travel time. Even if the model results shown by Daly et al. (2014) are sensitive to TTI, the use of this variable requires being refined. With the cost of TTI being critical to the determination of the modal shares, additional efforts should be directed at determining a rigorous methodology to calibrate this variable. Determining a mode-specific stepwise cost curve, which includes speed reduction potentials from several infrastructure investments at different costs, could be a promising but also time-intensive approach.

Pye and Daly (2015) overcome some of the limitations and challenges of the TTI in the bottom-up optimization model ESME. They incorporate the approach by Daly et al. (2014), with some differences and they restrict the study to urban passenger transport and to trips shorter than 55 km. Two new constraints are introduced to better represent modal choice: the maximum level of modal shift potential and the rate of modal shift for each mode, which are determined by considering the historic trip distance profiles. Moreover, an adjustment factor on the TTB (equal to 0.95 hours/person/day) is used so that average urban speeds do not have to increase despite increasing demand. An important distinction from Daly et al. (2014) is that infrastructure is still considered, but only restricted to its cost, to give a more comprehensive picture of the cost of the modes. Infrastructure investments do not lead to improvements in travel time associated with different modes. However, the model has to ensure that the sum of existing and new infrastructure is enough to accommodate the demand of mobility.

In the CGE model, IMACIM-R (Waisman et al., 2013) households derive utility from the consumption of goods and from the use of mobility services provided by four main transport modes (air, road, public, and non-motorized). The value of the utility function is maximized while subjected to two constraints:

- i. A standard budget constraint, which trades-off between transport-related expenditures and consumption of other goods.
- ii. A time budget constraint (TTB), which restricts the demand for transportation services purchased by households, taking into account that the speed of each mode is associated with the utilization rate of that mode (i.e., congestion effect). The induction effect of infrastructure deployment on mobility demand (TTI) is therefore addressed: an expansion of the infrastructure network makes modes faster, allowing households to travel more with equal time budget.

The main advantage of the TTB method consists in not requiring additional data but simply in introducing a general constraint to the problem. The concept of TTB has been criticized since it conflicts with utility maximization, or with the principle that travel is a derived demand. Additionally, it has been argued that TTB is constant at an aggregate level while large differences may emerge as soon as one starts disaggregating populations in demographics, travel types, and different spatial areas (Mokhtarian & Chen, 2004).

4.2.2.2. Discrete choice models. Within the 12 models reviewed which features modal choice representation, four adopt a discrete choice model to predict the choice probabilities of the different transport modes on the basis of travel time and travel cost, with GCAM (Kyle & Kim 2011) accounting only for travel cost. In the hybrid model CIMS (Horne et al., 2005), an MNL model has been built from surveys in which respondents were asked to select among five modes (driving alone, carpooling, taking public transit, using a park and ride service, and walking or cycling), defined by the attribute travel time, cost, pick-up/drop-off time, walking/waiting time, number of transfers, and bike route access. Subsequently, survey data have been translated into parameters of the utility functions, used in CIMS through Equation (4).

In the bottom-up simulation model TRAVEL, a NMNL model calculates the mode shares on the basis of a mode cost $Cost_{r,m,t}$ (for every region r , mode m , and time t), where both travel cost and travel time are included (Equation 5).

$$Cost_{r,m,t} = k_{r,m,t} * CostPerKm_{r,m,t} + TimeWeight_{r,m,t} * TimeUse_{r,m,t} \quad (5)$$

Equation (5) presents two balancing parameters: $k_{r,m,t}$ is an adjustment factor for non-monetary differences in the total cost of different modes while $TimeWeight_{r,m,t}$ describes the relative importance of time and cost. This factor is endogenous to the model: if the total travel time per capita

exceeds the TTB (assumed equal to 1.2 hours/person/day), the time factor $TimeUse_{ser,m,t}$ is awarded a greater weighting (Girod et al., 2012).

In the model MESSAGE-TRANSPORT (McCollum et al., 2017), mode switching decisions are taken via a logit-based algorithm. The passenger travel demand projections split by mode are endogenously determined as the product of the total regional travel demand by the modal share for each mode, region and time, through MNL probabilities. These are expressed as the sum of fuel price, non-fuel price, and a time element.

Advantages and disadvantages of discrete choice models in representing modal choice are the same as those for including technology choice previously discussed. In particular, it is interesting to notice that the concept of TTB can be easily integrated in this methodology, as, for example, in the model TRAVEL (Girod et al., 2012).

4.2.2.3. Constant elasticities of substitution. As for technology choice, modal choice can be modeled through CES. Examples of models using such approach are EPPA (Karplus et al., 2013), PRIMES-TREMOVE (E3MLab, 2014), and ReMIND (Pietzcker et al., 2010). In the latter study, the different transport modes are formulated in a nested CES structure while at the lowest level of the tree diagram the technologies in each transport mode are represented with linear production functions. CES functions first regulate the substitution between freight and passenger transport, then between on-land, maritime and aviation, and finally between rail, truck, urban cars, intercity cars, and bus. This nested structure was developed according to the level of linkage of the transport services and the ease of mode replacement.

The model UKTCM (Brand et al., 2012) endogenously determines modal shares using elasticities: modal choice is modeled by linking through dynamic elasticities travel demand for each mode to vehicle ownership and operating costs, as well as to GDP and number of households.

As previously discussed, the CES methodology can be best applied within a top-down framework and the values for the CES functions are typically estimated.

4.2.3. Driving pattern

Five of the models analyzed introduce the concept of driving pattern at different levels of detail. There are two main methodologies adopted: driving profiles and elasticities. Modeling driving pattern relates to taking into account the variable speed of modes and technologies, which can be associated with different levels of energy consumption and emissions. Intercity and urban transport have different impacts on energy use and CO₂ emitted (Schäfer, 2012). Fontaras, Franco, Dilara, Martini, and Manfredi (2014) investigated the correlation between driving profiles and CO₂ emissions, determining that the highest emissions occur over urban conditions, reaching up to 290 g/km and 158 g/km for gasoline and diesel cars, respectively, whereas the lowest occurred over extra-urban or rural conditions (averaging at 133 g/km and 107 g/km for the two fuel types examined).

Sectoral transport models (T) generally include a disaggregated geography of the transport system and calculate travel speed as an endogenous variable. These simulation models determine modal speed by allocating the endogenously generated transport demand split by modes to the road network, taking into account the infrastructure capacity and congestion. Moreover, modal speed is reiterated to the modal choice module, which recalculates the modal shares accounting for the travel time of each mode.

In PRIMES-TREMOVE (E3MLab, 2014), vehicle types are grouped into classes according to different driving profiles. COCHIN-TIMES (Bunch et al., 2015) and MESSAGE-TRANSPORT (McCollum et al., 2017) consider consumer heterogeneity, with yearly driven distance (a proxy for speed) as one classification criteria. IMACIM-R (Waisman et al., 2013) contains a stylized representation of the relationship between infrastructure deployment (in terms of total vehicle capacity), modal demand, and modal speed. In EPPA (Karplus et al., 2013), elasticities capture the relationship between fuel price, vehicle efficiency, and mileage.

Disaggregating mode and vehicle speed at a greater detail would enable a better representation of fuel consumption and CO₂ emissions in the transport sector. While most of the energy system models already introduce the segmentation between urban and intercity transport (e.g., PRIMES-TREMOVE (E3MLab, 2014)), thereby allocating different energy efficiencies and emissions factors to the two alternatives, driving patterns have not been fully included yet. The reason for this lack of representation is most probably due to the modeling challenges and high computational time associated with great geographical/speed detail. In fact, a route assignment module is needed to represent speed endogenously, in turn requiring the description of the road network. Further modeling of driving patterns can be addressed through data collection from vehicles that track driving data, for example, speed and distance, harnessing the potential of big data analytics (Hawelka et al., 2014). This method can allow for the integration of data sets describing the real behavior associated with driving profile, fuel use, or time of use. On the other hand, a limitation lies in the uncertainty around the availability of such data.

4.2.4. New mobility trends

Among the models reviewed, only one deals with new mobility trends, specifically addressing carpooling. As introduced in Section 4.1, new mobility trends refer also to increasingly recurring phenomena such as car sharing systems, autonomous vehicles, and optional transport abdication connected to teleworking.

CIMS regards carpooling as an additional mode, selected among the various alternatives based on multinomial logit probabilities (Horne et al., 2005). In this way, the ratio between car drivers and car passengers is determined by choice probabilities considering capital costs, fuel costs, weighted average travel time, and some intangible costs reflecting the perceived benefits or drawbacks of using a certain technology.

A possible option for modeling carpooling is to account for vehicle occupancy factor by analyzing the relationship of this variable with population characteristics such as age, gender, income, and travel type. Additionally, survey-based data on the acceptance and use of this service can be integrated through virtual technologies in an optimization model, where cost and efficiency of the technologies represent the cost and efficiency of a potential promoting campaign. The potential of adopting a car sharing system for reducing the environmental impact of the road transport sector has been also assessed through a case study in the city of Montreal (Sioui, Morency, & Trépanier, 2013): the promising results show that there is a 25% difference in the modal share of car use between a person with full access to a car and a high-frequency user of the car sharing with no car.

Autonomous vehicles may affect energy consumptions and emissions in a broad spectrum of ways, both positive and negative. Wadud, MacKenzie, and Leiby (2016) explore the net effects of automation on emissions, considering phenomena such as platooning, eco-driving, congestion, improved crash avoidance, travel cost reduction, and new user groups. Results show that many potential energy-reduction benefits may be realized through partial automation while the major downside risks appear more likely at full automation. However, robust conclusions cannot be drawn, as there is a high level of uncertainty on the evolution of the phenomena. Different prospects of users' behavior toward this technology could be incorporated in E+T models, as to support the investigation on the mitigation potential of autonomous vehicles.

Generally, new mobility trends do not find a sufficient representation in the models reviewed. Nonetheless, there are growing efforts in the international energy and transport modeling community toward a better understanding of the concept of Mobility as a Service (MaaS) and the impact it may have on the future transport system (Kamargianni, Li, Matyas, & Schäfer, 2016).

5. Conclusion and recommendations

This paper analyzed 27 integrated energy and transport models and created a taxonomy for these various model types⁶. This paper reviewed the methodologies adopted for introducing behavioral features related to consumer purchase, adoption, and use of transport technologies with the purpose of addressing two questions: (i) how should transport and energy models be structured to allow an effective inclusion of behavior and (ii) what key attributes and parameters should be introduced to represent transport-related consumer choices in an integrated energy and transport model. Relating to the former question, the authors' conclude that there are three common approaches for structuring a model to improve the representation of behavior—top-down, bottom-up, and hybrid structures—each of which

have advantages and disadvantages depending on the scope and purpose of the model analysis. Nonetheless, soft-linking and novel approaches recently developed (Section 4) emphasize a bottom-up model structure as the most flexible and promising method. Concerning the latter question, this review identified technology choice, modal choice, driving patterns, and new mobility trends as the key features to correctly depict transport behavior in integrated energy and transport models (E+T). Furthermore, the authors recommend heterogeneity, travel time budgets, and driving profiles as the key attributes and parameters to be introduced in E+T models to represent such behavioral features.

5.1. Structure

Top-down (TD) models examine the entire economic system in a detailed way and constitute a valid tool to simulate the economic mechanisms that regulate technology substitution. They can be used to endogenize modal or vehicle choice and to answer research questions concerning the relationship between modal/technological demands and fuel/electricity prices. Nonetheless, having the economic sector as the core and focus of the model, TD models may fail at including a comprehensive set of fuels, vehicle technologies, and modes. The attributes characterizing the different transport alternatives are often rendered to a low level of accuracy and TD models are less capable at directly capturing the effect of changes in efficiency, mileage, and occupancy factors, relative to BU models. Further efforts are required to bring such models to a technologically rich format, as done by Karplus et al. (2013).

On the contrary, *bottom-up (BU)* models more suitably analyze the effect on the overall energy system of certain exogenously imposed modal/technology shares. As long as vehicle market shares are exogenous assumptions, pure BU models prove to be a valid policy analysis tool. Inversely, to endogenously determine behaviorally realistic market shares, the BU framework needs to be upgraded by adding new variables or by linking it with external transport-focused models, of the T or T+ types.

Hybrid models join and harness the advantages of BU and TD frameworks, thus proving more capable at capturing many of the behavioral features discussed. They are valuable at answering research questions investigating both the energy sector and the surrounding economy. However, the structure of this class of models is inherently more complex when compared to pure BU or TD models, potentially creating issues with computation. The model comes as a “single-package,” not separable into the TD and BU components, thus limiting the flexibility of its use.

Of the three structures outlined above, the authors regard BU models as the most promising approach to include a representation of behavior in E+T models. The benefit of representing behaviorally realistic choices directly within an energy system model is manifold. First, these improved BU models allow for energy system-wide considerations. Second, they support our understanding of the future reciprocal implications of decisions taken in the transport and energy

⁶Sectoral energy models (E), energy models partially including the transport sector (E+), highly integrated energy and transport system models (E+T), transport models partially including the energy sector (T+), and sectoral transport models (T) (see Section 3).

systems. Third, a much wider variety of policies can be assessed through the E+T framework, as further discussed in Section 6. Because BU optimization models do not originally represent behavior, either they need to be soft-linked with an external transport simulation model which has a predefined representation of behavior, and uses a complementary mathematical method, or their structure needs to be adjusted to accommodate the new behavioral features. The former approach makes the model flexible—whenever the analysis is not purely transport focused, the energy system model can run in standalone mode with a simplified representation of the transport sector. The latter approach is further discussed in Section 5.2.

5.2. Parameterization

Technology and behavior measures have been identified as critical measures in addressing transport CO₂ emissions, in particular, avoiding, shifting, and improving (IEA, 2012). For this reason, this paper aimed at identifying the most suitable method(s) of representing technology choice (improving), modal shifting (shifting), and both driving patterns and new mobility trends (avoiding) in E+T models.

Including heterogeneity was regarded as the best means of improving the representation of *transport technology* choice. Traditional BU energy system models assume homogeneous consumers taking perfectly rational decisions. Introducing heterogeneous decision-makers is a precondition for incorporating behavior in E+T models. Heterogeneous transport users have different preferences, resulting in a wide portfolio of technologies chosen, each one optimal for a specific consumer group. When deciding the number of dimensions along which consumers are split and the number of behavioral features to consider, a compromise between model complexity and completeness needs to be made. An ideal representation of transport behavior within an E+T model would involve representing all consumers within the region in question, yet the computation power required for this level of detail renders this method incredibly onerous. To avoid intractability or excessive complexity of the model, efforts have to be addressed toward determining the minimum number of dimensions and subgroups necessary and sufficient to distinguish the main consumer groups in an exhaustive way.

Of all approaches reviewed regarding *modal choice* representation, travel time budget (TTB) is recommended as the best method of modeling this feature within BU models. It can be introduced by adopting literature values (Schäfer & Victor, 2000) or eventually more region-specific TTBs, available from national travel surveys. Moreover, the concept can be easily incorporated in the model, requiring only the definition of modal speed and the setting of a constraint (as in Daly et al. (2014) and Pye and Daly (2015)). An interesting area for future work would be to adapt the methodology proposed by McCollum et al. (2017) and Bunch et al. (2015) to cover modal choice in BU optimization models. To provide reliable modal shares and calibrate the intangible costs suitably, the energy system model requires drawing data

from a detailed support model (e.g., of the T type) that incorporates modal choice.

We also acknowledge the need to model *driving patterns* at a detailed geographical level to accurately account for fuel consumption and emission factors from vehicles, which strongly depend on the driving performances. The authors recommend using the virtual technology approach for simulating the introduction of eco-driving behavior through promoting campaigns. These campaigns and their effectiveness on changing car users driving behavior, along with the improved fuel consumption and emissions, can be directly reflected through virtual technologies within a BU optimization framework. The relationship between modal speed and infrastructure could be incorporated in the integrated energy and transport model as was carried out in the model IMACIM-R (Waisman et al., 2013). Another possible method consists in adapting the approach by Ramea, Bunch, Yang, Yeh, and Ogden (2016), where the congestion level, and thus the modal speed and emission factors, is determined in an iterative way as a function of the infrastructure capacity.

Modeling *new mobility trends* offers the opportunity to explore and unlock their potential in contributing to more sustainable transportation systems (Grischkat, Hunecke, Böhler, & Hausteine, 2014; Wadud et al., 2016). Car sharing services can possibly be modeled by introducing a new car technology type characterized by a higher mileage per year. Carpooling can be incorporated in integrated energy and transport models by considering a lower car-ownership level and higher occupancy factors.

6. Discussion

All models share the common trait of attempting to represent some aspects of a system as accurately as possible. Despite this, the representation of behavior in integrated energy and transport models, or lack thereof, has led toward potentially misguided analyses. From a policy perspective, improving the modeling of transport behavior represents a step forward in supporting the analysis and definition of more targeted and effective transport and energy measures. The increased level of detail in the representation of the transport sector allows studying the cost and impact of specific policies, possibly diversified for each transport technology, mode or consumer group.

Regulatory and market-based strategies with a clear and quantitative definition of their economic effects and temporal applications could be tested through the improved optimization and simulation models. On the other hand, softer measures, typically informational or voluntary-based programs (Richter, Friman, & Gärling, 2011), include a more descriptive specification and are therefore less applicable to these models.

When the model contains an advanced incorporation of transport *technology choice*, costs and other non-monetary parameters characterize the vehicle technologies. Additionally, the segmentation of consumers according to their attitude toward car purchase and use allows addressing

tailored strategies for supporting the transition to a more sustainable transportation system. For instance, the model can test the effectiveness of subsidies incentivizing the purchase of electric vehicles, now considering a heterogeneous group of potential vehicle purchasers. The system cost of the introduction of “feebate” schemes, that is, a combination of rebates awarded to purchasers of low-carbon emission vehicles and fees charged to purchasers of less efficient vehicles (Sims et al., 2014), could be computed as well. Moreover, models could analyze the impact of public investments in the refueling infrastructure of electricity and low-carbon fuels on the adoption of new car technologies.

The possibility of endogenously determining the market shares of the *modal choice* enhances the analysis of a large set of measures promoting the shift from private to a more efficient mode of transport: national and regional strategies targeting investments in public transport infrastructure (e.g., dedicated bus lanes), decrease in public transport cost, fuel and vehicle purchase taxes, road-pricing, vehicle restrictions, and parking reforms in cities.

Although few of the models reviewed include a comprehensive incorporation of *driving patterns*, some of them attempt to model the relationship between infrastructure investment and mode market shares while others segment vehicle users into different groups according to their driving profile. These models can aid the definition of, respectively, strategies for improving the urban traffic management (e.g., speed limits) and eco-driving programs affecting driving behavior. Finally, the inclusion of *new mobility trends* (or Maas) could allow the assessment of strategies promoting vehicle sharing services and the spread of carpooling adoption, along with the impact of transport demand reduction as a consequence of teleworking (Cohen-Blankshtain & Rotem-Mindali, 2016).

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**TIMES-DK: TECHNOLOGY-RICH
MULTI-SECTORAL OPTIMISATION
MODEL OF THE DANISH ENERGY
SYSTEM**

TIMES-DK: technology-rich multi-sectoral optimisation model of the Danish energy system

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Abstract

As Denmark progresses towards a carbon neutral future, energy system models are required to address the challenges of the energy transition. This article describes design, input data and current usage of TIMES-DK, the first Danish energy system model that includes the complete national energy system, covering long-term technology investments. The article aims at explaining the modelling approach; highlighting strengths and reflecting upon limitations of the model; illustrating possible applications of TIMES-DK and inspiring new model developments. Some of the key strengths of the model include simultaneous optimisation of operation and investments across the complete energy system over the whole modelling horizon, explicit representation of the most important sectors of the economy, modular structure and the possibility of linking to a computable general equilibrium model for an additional insight on, e.g. public finance or CO₂-leakage. TIMES-DK is being developed in close collaboration between an energy agency, a university and a consulting firm, to improve its robustness, relevance and impact on policy making. It allows for a wide range of applications including exploratory energy scenarios and policy analysis. To meet challenges of the future, further development of the model is needed and consequently the article provides references to ongoing projects addressing current development needs, such as improved representation of transport and flexible handling of the temporal dimension. To support a democratic and transparent process around decisions for the future Danish energy system, TIMES-DK should become available to interested parties.

Keywords: energy systems analysis, TIMES model, Denmark, model description, model application, energy transition

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1. Introduction

Denmark is undergoing a transition with its energy system set to become carbon neutral by 2050 [1]. What the energy system will look like in the future remains an open question. To investigate this question, energy planners, policy makers, researchers and non-governmental organisations (NGOs) require adequate tools that could help them assess potential energy systems configurations and take into account the interaction between various sectors. These tools should be open and accessible to promote grassroots development, user-critique and to facilitate discussion on the future of the Danish energy system [2].

Several sector models with different perspectives and approaches on the energy system exist for Denmark. The Danish Energy Agency has been using a combination of models to cover all the sectors (e.g. RAMSES [3], EMMA [4], ElmodelBolg [5], COMPARE [6]). Landstrafikmodellen (LTM), a 4-step simulation model of the Danish transport sector [7], has been used to support planning and investment decisions in traffic infrastructure. The Balmorel model, used by private companies and in academia, is a partial equilibrium model for simultaneous optimisation of generation, transmission and consumption of electricity and heat [8]. Both energy models STREAM [9] and EnergyPLAN [10], used for scenario analysis, cover all the sectors, but lack endogenous investments. The Danish TSO (Transmission System Operator), Energinet, has a whole suite of models for analysing various portions of the power and gas systems [11].

The development of TIMES-DK was initiated from a growing need to be able to prioritise and describe socioeconomic optimal pathways to a low-emissions society across all economic sectors. Covering all sectors in one model would speed up the analysis process, while providing a consistent method of policy evaluation across sectors.

The literature covers a growing number of energy modelling tools, developed and applied at regional, national and international scale [12–15]. Bottom-up techno-economic models include the TIMES-MARKAL model family, with applications in several countries [16–18]; the open source energy system model OseMOSYS [19]; the global model MESSAGE [20]; and the energy model PRIMES [21], applied for the preparation of European energy outlooks and impact assessment studies. Integrated assessment models, such as GCAM [22] and IMAGE [23], include the representation of energy systems alongside the climate and ecosystem modules. The scenario-based modelling tool LEAP [24] is being used especially by developing countries to undertake mitigation emissions studies both in energy and non-energy sectors.

Based on the aforementioned past experiences in energy system model design, TIMES-DK was developed within the InterACT project [25] in close collaboration between the Danish Energy Agency (DEA), the Technical University of Denmark (DTU) and E4SMA. The model possesses the usual characteristics of the TIMES model family [26–28], such as being a bottom-up technology-rich energy system model suited for medium to long-term analyses. Although sharing the general design of other bottom-up energy system models, some of the distinct features of TIMES-DK include an improved representation of heat demands and heat saving measures by building type in the residential sector (Section 3.3), as well as a detailed industry modelling based on industry energy services rather than

technology type (Section 3.4). Additionally, quite uniquely, the energy system model was developed hand-in-hand with a computable general equilibrium (CGE) model, which enables easy linking of the models to investigate interactions between the energy system and the surrounding economy. To support a democratic and transparent analysis of future optimal pathways for the Danish energy system, the model development team is currently exploring the possibility of making TIMES-DK model and data available to all interested parties in the future.

The objective of this paper is to describe TIMES-DK and discuss its main strengths and weaknesses. Section 2 provides a concise model description including structure, temporal and spatial details, and main data sources. Section 3 presents a comprehensive overview of the sectoral representation, which includes supply, power and heat, residential, industry and transport sector. Section 4 describes existing and possible model applications. Finally, we discuss strengths and limitations of the model, including potential future development in Section 5.

2. Model Description

2.1. *TIMES Model generator*

The Integrated MARKAL-EFOM System (TIMES) model generator is developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP)², a Technology Collaborative Programme of the International Energy Agency (IEA), established in 1976. A TIMES model is based on the bottom-up approach [13, 29]. It is a single or multi-regional model, often with a technology-rich database, for medium/long-term analysis and planning of a national, regional or even city level energy system^{3,4}. In addition to that, TIMES is a techno-economic, partial equilibrium model-generator assuming perfectly competitive markets and full foresight (with the additional option of performing analyses under a myopic foresight mode by defining settings for a time-stepped solution). The TIMES model generator source code, written in GAMS, is open and available for download free of charge upon signing the ETSAP Letter of Agreement.

The TIMES models are based on welfare maximisation by minimisation of the total system costs discounted to the reference year, calculated as sum of investment cost, fixed and variable operation and maintenance (O&M) cost, import cost and export revenues for all the modelled processes. For a particular technology, its capacity remains until the end of its technical lifetime; in case the economic lifetime of the technology goes beyond the modelling horizon, its salvage value is deducted from the objective function. The type of inputs used to build the TIMES models are: exogenous service demand curves, supply curves, policies and techno-economic parameters for each technology. Supply curves show the quantities of primary energy resources (e.g. wind power) or imported commodities (e.g. oil and gas) available at a specific cost. The techno-economic parameters are assigned to currently

²ETSAP homepage available at: <http://www.iea-etsap.org>

³TIMES Documentation and Demo Models <http://www.iea-etsap.org/index.php/documentation>

⁴Example of TIMES applications <http://www.iea-etsap.org/index.php/applications>

available and future technologies, both transformation (e.g. wind turbine, gas boiler, heat pumps, district heating system, etc.) and demand technologies (e.g. electrical appliances, buildings by type and age, cars, etc.) that are converting one or more commodities into one or more other commodities (e.g. gas boiler transforms gas into heat for buildings that are delivering the demand commodity). Examples of technical parameters are efficiency and availability factor, while economical parameters include investment costs and interest rates. Policies include effects of legislation, such as taxes and subsidies on specific technologies or fuels.

The TIMES outputs are region-specific (for multi-regional models) and time-specific optimal investments, operation and import/export levels. Furthermore, alongside the optimal solution, the model output includes costs, environmental indicators, marginal prices of commodities and energy flows.

2.2. System overview

TIMES-DK is a multi-regional model, covering the entire Danish energy system. It is geographically aggregated into the two Danish power regions, i.e. Denmark East and Denmark West, with technological and economic projections until 2050. The model covers five sectors, namely: supply (SUP), power and heat (ELC), industry (IND), residential (RES), and transport (TRA). A detailed description of the sectors is given in Section 3.

Primary energy commodities can be either imported, exported or domestically extracted (SUP). Conversion technologies transform the primary commodities in secondary commodities (ELC), needed by the end-use technologies to satisfy the end-use sector service demands, i.e. for industry (IND), residential (RES), and transport (TRA). Furthermore, each energy commodity has associated respective emission factors, to account for the emissions produced from the combustion of fuels across all the sectors.

2.3. Geography

Denmark is divided into two regions, East (DKE) and West (DKW). Figure 1 shows the regions, along with the transmission lines connecting them and the interconnectors to the neighbouring countries. The latter are modelled as "price regions", i.e. they are represented by projections of available transmission capacities and electricity prices [30].

District heating (DH) producers in Denmark are characterised as Central and Decentral [31]. Accordingly, DH areas supplied by these producers are named Central and Decentral. Central DH areas are located in bigger cities, have higher installed capacities, more consumers and higher grid efficiency compared to Decentral areas. Central and Decentral DH areas are represented with dark blue and green polygons in Figure 1. Next-to-DH areas are sharing a border with DH areas. They are classified as Central or Decentral depending on the DH area they are located next to. Central and Decentral Next-to-DH areas are represented with lighter blue and green polygons in Figure 1. Individual areas are not sharing a border with DH areas and are located far away from existing DH areas. Individual areas are represented with red polygons in Figure 1. All polygons of the same colour and within each of the regions (DKE and DKW) are aggregated resulting in 5 heating areas per region in the model.

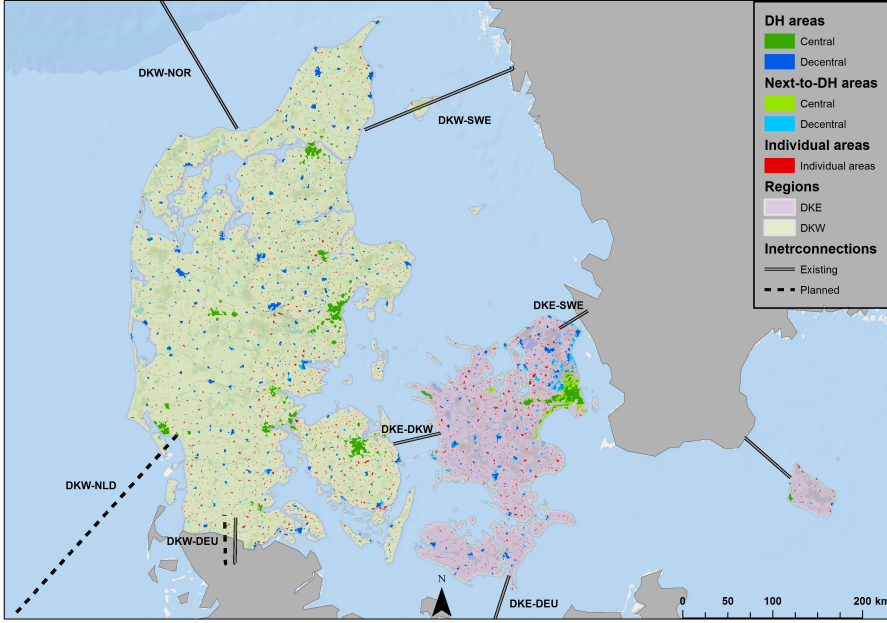


Figure 1: Geographical aggregation in TIMES-DK model, based on [30, 31]

2.4. Time

TIMES-DK is calibrated for 2010, i.e. the model output for the base year replicates the historical energy system of Denmark in 2010, as reported in the Danish energy statistics (for sector-specific data sources, the reader can refer to Table 1 and Section 3). The convergence to historical data has been established by aligning the aggregated capacities of conversion and end-use technologies to those reported in the statistics for 2010. The time horizon covers the years 2010 to 2050, and it is flexibly sub-divided into shorter application-specific model periods of various duration, most commonly 1-5 years. In turn, every year comprises 32 non-sequential time slices, representing seasonal (4 seasons), weekly (working/non-working days) and daily variation.

The division of a year into seasons aims to represent the change of the heating demands. The weekly division represents the difference in demand patterns (electricity, heating, etc.) between working and non-working days. On the daily time slice level, every hour of the year is classified into four categories according to the historical variability of renewable energy resources and power load profile. These four categories are intended to represent situations that are critical for the power system and include: A) "high wind production - low power demand", B) "high power demand - low wind production", C) "no photovoltaics

(PV) production” and D) ”rest”. Figure 2 illustrates the time slice structure adopted in TIMES-DK.

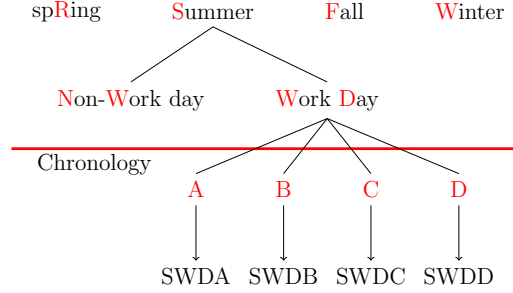


Figure 2: Time slice structure in TIMES-DK

The 32 time slices represents the most disaggregated resolution in the model, yet not all modelled parameters are defined at this level of detail. For instance, on the supply side, power and district heat production are generally defined on 32 time slices. On the demand side, the electricity and heating service demands in residential and industrial sector are defined at 32 time slice level, while the transport demands are defined at annual level.

The definition of the time slices is meant to capture especially the availability of variable renewable energy (VRE) in relation to demand in critical situations, following the methodology illustrated in [32]. This ensures that the model invests in sufficient back-up capacity to secure supply at any time. For VRE generation technologies, i.e. solar PV and wind, the production profiles are defined at 32 time slice level to describe their maximum availability in each time slice. Non-VRE power, e.g. a CCGT (Combined Cycle Gas Turbine), and heat production has no limited availability in the time slices and can therefore produce up to their installed capacity at any time. An exception is the production from solar heating plants: for solar DH plants, the production availability is defined on seasonal level because they are assumed to be connected to large heat storage while, for small-scale individual solar heating plants, the production availability is defined on the 32 time slice level. Furthermore, the efficiency of large scale heat pumps is defined on seasonal time slice level as it is assumed that the efficiency is dependent on the outdoor temperature. Import and export prices for electricity are modelled on 32 time slice level.

2.5. Main data sources

Table 1 illustrates the main data sources on which TIMES-DK is based. Many of those are regularly maintained data sets. Among them are energy technology catalogues, building register, Danish national travel survey and register of wind turbines. Relying on regularly maintained data sets significantly reduces the time needed to update the model, as well as simplifies the update process. Within each sector, data is typically collected from a consistent set of sources, as to maintain coherence in underlying assumptions on, e.g. cost

calculations. Harmonisation of assumptions across the full model is performed through verification of model results and calibration.

Table 1: Main data sources for TIMES-DK. SUP: Supply, ELC: Power and heat, IND: Industry, RES: Residential, TRA: Transport. O: Original data, P: Processed data

Data	Sector	Input used	Type	Reference
Energy plants	ELC	Costs, efficiency, availability factor, lifetime	O	[33]
Energy plants	ELC	Existing capacity	O	[31, 34]
District heating grids	ELC	Existing capacity, losses	O	[35]
District heating grids	ELC	Expansion potential, costs	O	[36]
Bio-refinery technologies	SUP	Costs, efficiency	O	[37]
Hydrogen technologies	SUP	Costs, efficiency, availability factor, lifetime	O	[38, 39]
Biogas plant technologies	SUP	Efficiency, costs	P	[40–43]
Fossil fuel prices	SUP	Import/export price	O	[44]
Biomass prices	SUP	Import/export price	O	[40, 45]
Electricity trade	SUP	Import/export price, transmission capacity, availability factor	P	[30, 46]
Transport technologies	TRA	Stock, mileage, occupancy load factor, mobility demand	P	[47]
Transport technologies	TRA	Stock retirement rate	P	[48]
Transport technologies	TRA	Travel pattern	P	[49]
Transport technologies	TRA	Efficiency	P	[50]
Transport technologies	TRA	Costs, efficiency improvement, lifetime	P	[50]
Fuel blending technologies	TRA	Minimum level, year	O	[50]
Stock of electrical household appliances	RES	Stock in the base year	P	[51]
Stock of electrical household appliances	RES	Projections of the stock	P	[52]
Residential building stock	RES	Heated area in the base year	P	[53]
Residential building stock	RES	Housing demand	P	[54]
Residential building stock	RES	Demolition rate	P	[55]
Residential building stock	RES	Energy performance of the existing stock, cost of heat savings	P	[56–58]
Residential heating technologies	RES	Costs, efficiency improvement, lifetime	P	[33]
Industry energy service demand	IND	Mapping of energy demand by sector	P	[59]
Industry technologies	IND	Energy service supply technologies	P	[31]
Industry energy savings potential	IND	Sectoral energy savings potentials and costs	P	[60]
Industry energy service driver	IND	Sectoral output projection	O	[61]
Emission factors	All	Emission factors by fuel type	O	[50, 62]

3. Sectors

This section details the sectoral representation in TIMES-DK. The description follows the flow of the energy commodities, from the extraction/import/export of primary energy commodities in the supply sector, through the conversion in power and heat or in other energy commodities required to fulfil the energy service demands of the end-use sectors, i.e. residential, industry and transport.

3.1. Supply

The supply sector in TIMES-DK comprises all the activities related to import/export and extraction of primary energy resources, both fossil and non-fossil, the conversion of these into secondary energy commodities (i.e. bio-fuels, hydrogen and oil products), and their delivery to the downstream sectors. More specifically, the supply sector includes both the domestic extraction of oil and gas, imports and exports of solid, liquid, gaseous energy commodities, as well as electricity traded with the neighbouring countries.

Considering that Denmark has little influence on the price for the globally traded energy commodities such as crude oil, natural gas and wood pellets, these are imported from or exported to a single geographical region, hereafter called Rest of the World (ROW). Since ROW is not modelled in TIMES-DK, exogenous import and export prices ([40], [44], [45]) are the parameters regulating the energy commodity exchange with ROW (Figure 3).

On the other hand, the power trade with neighbouring countries and within the modelled regions, is represented at a high level of detail, to account for region-specific import/export prices of electricity, capacities and availability factors of transmission lines. These comprise connections with Germany, Norway, Sweden and Netherlands. The import/export prices of electricity from/to neighbouring regions are adopted from [30]. Moreover, we include the intra-regional exchange of electricity between the two regions, DKE and DKW. The exchange is limited by the existing installed capacity and takes into account losses of an HVDC (high-voltage direct current) interconnection.

The procured primary energy commodities are transformed into secondary energy commodities through conventional crude oil refineries, bio-refineries and hydrogen production technologies. Some of these technologies produce electricity and/or heat, which can be used for DH, as a by-product in addition to their primary output. Table 1 reports the data sources, i.e. technology catalogues and scientific publications, used for the characterisation of the different technologies in terms of required inputs, costs, efficiencies, plant lifetime and availability factors. The secondary energy commodities are delivered to downstream conversion sector (ELC) and end-use sectors (IND, RES and TRA), as shown in Figure 3.

The national energy balance, providing information on the energy supply mix and the domestic reserves of oil and gas, supports the calibration of the supply sector in the base year.

3.2. Power and heat

The power and heat sector in TIMES-DK is responsible for producing electricity and district heat. These secondary commodities are delivered to consumers via the transmission and distribution networks. The installed capacities of the facilities, grouped by size,

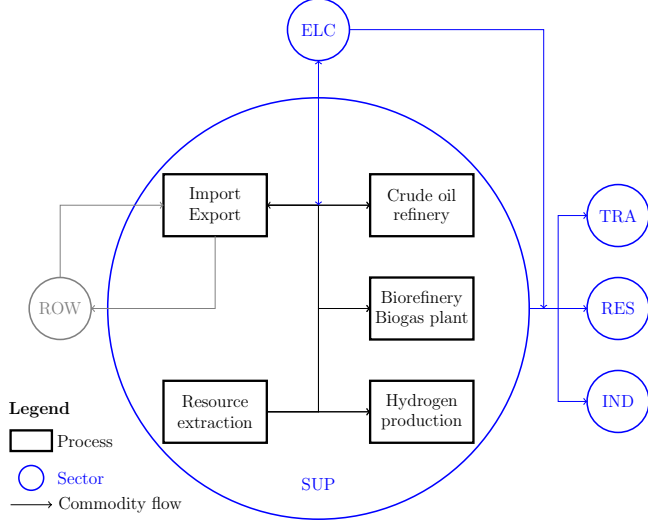


Figure 3: Schematic of the supply sector and its linkages with other sectors.

type and location, describe the state of the power and heat system in the base year. The retirement profile, i.e. the share of the base year stock [31, 34] that is decommissioned in each model period, is specified for each technology group. For the existing DH grids, the base year capacities were obtained from [35]. The existing production facilities are characterised by techno-economic parameters, such as efficiency, fixed and variable O&M costs and availability factors [33].

In addition to the existing stock of technologies, the model can invest in a set of new technologies in the future years. These are therefore also described with an investment cost [33]. Furthermore, we model potentials of renewable energy sources, including domestic biomass potentials [63–65].

TIMES-DK does not take into account the need for spinning reserves, inertia in the system, frequency control and other auxiliary services. Ramping of power plants and unit commitment is also not considered. This makes it computationally easier for the model to balance the system at any time slice, while it might overestimate the flexibility of the system. To overcome this issue, complementary models with higher temporal resolution and higher level of technical details, such as Balmorel [8] or EnergyPLAN [10], can supplement information on more realistic availability factors for the most critical technologies.

3.3. Residential

The residential sector comprises all the activities related to satisfying household heating (space heating and hot water) and electricity (operation of appliances) demand. The heating

tems are located in larger cities, have higher installed capacities, more consumers and higher grid efficiency compared to decentral systems. Residential buildings within or close to these areas include DH among their heat supply options. All the remaining residential buildings belong to individual areas, i.e. without access to DH. As a result, we classify the residential building stock into 36 groups, as presented in Appendix A.

The heated area of residential buildings in the base year is adopted from the Danish Building and Housing Register (BBR) [53]. After the base year, the change in the heated area in the residential sector drives the heat demand. The construction rates are calculated for each of the 36 building groups as a difference between housing demand [54] and existing stock affected by demolition [68]. We assume that the heating demand of new buildings complies with building regulations [55].

Heat saving measures in the residential sector reduce heating demand proportionally to heating degree-days. For each of the 36 building groups, we use heat saving cost-curves that are calculated based on the cost of replacing building envelope elements (floors, walls, roofs, windows and ventilation systems) and their lifetimes [69]. The data about existing stock and cost of heat savings are obtained from [56–58]. Heat savings are not available for new buildings.

The energy service demand for electrical appliances is represented by the following 7 demands: computers, cooking, entertainment, lighting, refrigeration, machines (such as washing) and others. Electricity demand generated by household appliances depends on the ownership level and specific consumption. These, as well as the stock of appliances in the base year and its development in the future are based on ElmodelBolg Statistik [51] and ElmodelBolg Prognose [52]. The projection of the specific energy consumption takes into account that efficiency of the appliances is increasingly determined by EU regulation, i.e. the Ecodesign and the Energy Labelling Directives. The ownership level is informed by historical trends that are projected into the future.

3.4. Industry

Industry energy service demands are modelled at a very disaggregated level in terms of twelve different economic sectors (covering primary, secondary and tertiary sectors) namely: 1) agriculture, forestry, fishing, gravel and stone; 2) food, beverages and tobacco; 3) chemicals (excl. manufacture of basic metals); 4) metals, machinery and transport equipment; 5) cement and bricks, glass and ceramics; 6) other commodity production; 7) wholesale and retail trade; 8) private service (incl. support for transportation and postal activities); 9) public service; 10) construction; 11) other utilities; and 12) motor vehicles - purchase and repair. Energy service demand is based on a comprehensive study [59], which creates a correspondence between historic fuel demands and sectoral energy service demands. Figure 5 illustrates the structure of the sector-specific energy service demands in TIMES-DK. The brackets in Figure 5 denote the boundaries of the industry sectors (IND).

Energy service demand in TIMES-DK is best understood as the net energy demand associated with the particular type of energy service. This approach is somewhat different from other TIMES models, where energy service demands are often modelled in terms of specific sector outputs, e.g. tonnes of cement or tonnes of steel to be produced. However,

with relatively few large energy-intensive firms in Denmark, modelling the actual material output has a limited scope in a Danish context. Instead, defining energy service in terms of net energy demand offers a consistent and scalable method for modelling energy service demand across very different sectors.

As a consequence, high temperature process heat in the agriculture sector will be different from high temperature process heat in the concrete sector. This difference is captured as we account for the fuel specific capacity mix of producing each individual energy service in each sector, i.e. the share of coal in high temperature process heat is significantly higher in the concrete sector compared to the agricultural sector. We calibrate TIMES-DK by endowing the model with fuel specific energy service capacities such that the stock of these in combination with efficiency and availability assumptions matches historic fuel demand for each sector.

In future modelling years, the energy service demand can either be supplied by investing in fuel (and energy service) specific (conversion) capacity or reduced through energy savings. New conversion technologies are specified with an efficiency and investment, variable and fixed cost based on technology catalogues [62]. Energy savings potentials for each sector and energy service are specified from a bottom-up study [60], which covers both the assessment of potentials and associated investment costs. The choice between investing in conversion technology and energy savings can be determined by TIMES-DK as part of the least-cost solution. As driver for the sectoral energy service demand we use economic projections on a sector level based on the Danish Convergence Programme [61]. We assume that the relative share of different energy services in a given sector remains constant in the future.

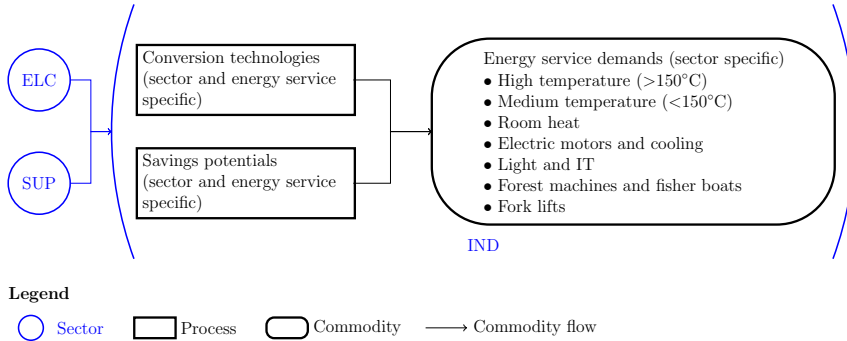


Figure 5: Schematic of sectoral energy demand in TIMES-DK

3.5. Transport

From an energy system perspective, transport can be considered an end-use sector, as it consumes secondary commodities (e.g. oil products, electricity, hydrogen and bio-fuels) to fulfil the end-use travel demands (e.g. passenger mobility and transport of goods). In

TIMES-DK, the transport sector comprehensively describes the Danish mobility demands and the end-use transport technologies. This sector includes passenger and freight transport, further split into aviation, maritime and inland sub-sectors. The two former include passenger and cargo aircraft, and ferry and cargo ship. The inland freight sector comprises three modes: van, truck and train. The inland passenger sector is represented with a high level of detail and includes eight modes: car, bus, coach, rail (metro, train, light-train), 2-wheelers (motorcycle and moped) and non-motorised modes (bike and walk).

The end-use demands of mobility are defined exogenously for each mode, from the base year until the end of the modelling horizon. They are expressed as service demands, respectively in passenger-kilometre and tonne-kilometre for passenger and freight transport. Moreover, the modes have associated more than one demand: for inland transport, the total modal demands are split by class of distance range (extra short/short/medium and long distances for passenger transport and short/long for freight transport) and for aviation and maritime transport demands are split between national and international.

The technology database for the transportation sector of TIMES-DK includes existing technologies and technologies that are available for future investments. These technologies compete to meet the projected travel demands. It is worth noticing that technologies can compete within a mode, but not between modes (i.e. modal shift is not possible). Several fuels are available to the transport sector, some of which make the transport sector integrated with the rest of the energy system (e.g. bio-fuels, electricity and hydrogen). Blending of bio-fuels and fossil fuels is achieved through blending processes characterised by increasing levels of bio-fuel shares over the modelling horizon.

Table 1 provides an overview of the parameters characterising the transport technologies in TIMES-DK. The techno-economic parameters describing the technologies are exogenously determined and change over time. Some parameters (stock, occupancy, load factor, mileage and efficiency) are also differentiated at the geographical level to represent regional differences in the transport sector between DKE and DKW. Generally, costs and efficiencies of new technologies available for investments are described with exogenous technology learning curves. End-use transport technologies are also characterised by specific travel patterns, which define their contribution to the different distance-range modal demands. A feature that distinguishes the car mode is the presence of a Weibull-distribution-based scrapping curve, which describes in detail the retirement profile of the base year vehicle stock. The retirement profile is based on historical observations of private vehicle scrapping in Denmark [48].

4. Model application

Given the inherent uncertainty of long-term analysis, eventually coupled with lack of robust and comprehensive data, energy system models do not aspire to predict the exact evolution of the energy system. Rather, they primarily support policy- and decision-makers in identifying effective policies by comparing a number of potential future pathways. Similarly, the energy system model TIMES-DK is capable of acting as a decision-making tool by providing insights into the dynamics of the different sectors of the Danish energy system.

But most of all, a complete model of the Danish energy system gives the possibility to analyse what measures are the most economically efficient across all sectors, e.g. when aiming at changing the whole energy system to be independent of fossil fuels. On the contrary, sector-based models fail at capturing cross-sectoral synergies and limitations.

TIMES-DK is currently used in a multitude of roles at the Danish Energy Agency. The model is part of the model suite used to produce Denmark's Energy and Climate Outlook [1]. It further serves a role as an in-house modelling tool to better understand the challenges posed by the Danish transition to a low-carbon economy. Finally, it contributes to assessing the impacts of different energy policy changes in the medium to long term.

Utilising the model for the creation of *policy* scenarios allows evaluating whether the energy system can reach desired targets and what set of measures are the most effective, e.g. comparing frozen policy scenarios with the implementation of a new set of policy settings [70], such as: enforcement of efficiency standards for, e.g. private vehicles; application of thermal insulation in residential buildings; phasing out of less efficient and more polluting technologies in the heat and power sector; and introduction of energy/emission taxes and investment subsidies on specific fuels and technologies. In this respect, TIMES-DK has been applied to assess future scenarios for the inland passenger sector, under different sets of policies [71, 72]. The TIMES-DK model can further be utilised for evaluating how uncertain parameters determine the possible future configurations of the energy system. Under this set of studies, TIMES-DK has been used to, e.g. analyse the competitiveness of technologies [73–75] under different economic assumptions, and assess the conditions guaranteeing or undermining energy security.

4.1. Linking to the CGE model

In parallel to TIMES-DK, a Computable General Equilibrium (CGE) model for Denmark, as well a soft-linking methodology, have been developed. Soft-linking TIMES-DK with the CGE extends the scope of the analysis by making it possible to capture structural adjustments in the economy as well as GDP and consumer utility effects from energy and climate policies. In addition, soft-linking provides insights related to issues such as public finance and CO₂-leakage from domestic energy and climate policies.

The foundation of our soft-linking strategy is that TIMES-DK provides the price of energy services, energy service fuel cost shares and future fuel tax rates to the CGE model. Based on this information, the CGE model then determines the energy service demand response, which is then fed back to TIMES-DK. The models iterate in a fully automated setup until the fuel cost associated with each energy service is equal between the two models (3-5 iterations). Fuel costs is an ideal convergence criterion, since it is equally and well defined in both TIMES-DK and the CGE model.

To facilitate an efficient soft-linking routine, data harmonization and the creation of a parallel structure between TIMES-DK and the CGE model with respect to energy services was required, i.e. the energy service demand in the CGE model mirrors the structure of energy service supply in TIMES-DK. For this purpose, the 12 final energy demanding industry sectors are defined in TIMES-DK based on the same national account definition used in the CGE model. On the other hand, the CGE model was designed to accommodate

the energy service modelling described in TIMES-DK for the residential sector. For a more detail description of the methodology, the reader can refer to [76].

5. Discussion

5.1. Strengths

The optimisation model TIMES-DK is used for analysing the medium- and long-term evolution of the Danish energy system under a specified set of constraints. First, the optimisation of the total system cost is a simple yet well-defined objective, allowing the accounting of present and future techno-economic characteristics of supply, conversion and end-use energy technologies. The resulting optimal solution represents a cost-effective configuration of the system, under the envisioned technological development and imposed policy and technical conditions. This relatively simple functioning logic affords quick cause-effect assessments, by investigating the impacts of changes in the input assumptions on the energy system.

Second, the inclusion of the most important sectors of the economy (see Section 3) allows examining the interplay between supply-side and end-use sectors from a system perspective. Since commodities such as fuels, electricity and heat are shared resources across sectors, limited availability of these (triggered by, e.g. installed plant capacities or expensive import prices) would clarify the existing synergies and competition between sectors. Similarly, following the imposition of an overall carbon budget in a target year, the model would illustrate the burden shifting among sectors along the modelling horizon in a techno-economic perspective.

Third, given the modular structure of TIMES-DK, it is rather simple to perform model expansions, especially in terms of new technologies and sectors. For example, carbon capture and storage (CCS) technologies are currently not implemented in TIMES-DK. However, their introduction does not require structural changes to the model, which can be expanded to accommodate CCS technologies as future investment options. Similarly, the user can adjust the time resolution, including modelling horizon, milestone years and time slice definition, according to the requirements of the performed analysis. From this point of view, TIMES-DK presents similarities with other bottom-up energy system models [16–18], with respect to, e.g. the flexible modular structure, the sector coverage and the rich technology representation. On the other hand, as explained in Section 3, the availability of detailed datasets and the relevance of analysing specific research questions for the country, drove towards a more detailed modelling of some sectors, e.g. residential, industry and representation of bio-fuels production.

Fourth, the collaborative model development shared between two main energy system modelling groups, i.e. Energy Systems Analysis (DTU) and Danish Energy Agency, has driven firstly the build-up and secondly the continuous update and expansion of TIMES-DK. This type of cooperation presents several advantages: data review, version control and documentation [77]; transparency, robustness and validation of input assumptions [78]; interdisciplinarity, e.g. sector and technology specialisation; impact on and relevance to policy making [77]; and managing structural uncertainty [79].

Finally, TIMES-DK benefits from the continuous development of the TIMES model generator carried out by the ETSAP community, as well as know-hows and insights generated within the community through the application of the TIMES models in the various parts of the world.

5.2. Limitations

Since all models are simplified representations of reality and its complex dynamics, they inherently bear limitations on the detail and scope of their mathematical representation [80]. Likewise, TIMES-DK includes simplifications with regard to, e.g. time and spatial resolution; at the same time sector and system boundaries partially restrict the breadth and depth of the possible analyses.

To avoid long computational times, the number of time slices in TIMES-DK is limited (Section 2.4), thus not allowing for a detailed temporal representation of the end-use demands and the availability of natural resources. While the time slice definition currently adopted carefully represents some critical occurrences for the power and heat sector, the absence of chronological time slices at the week and day levels prevents a detailed modelling of storage technologies. However, modelling of seasonal storage technologies is possible with the current structure of the times slices. Structural changes are made in the model within the SHIFT Project⁵, which will allow changing the time slice structure to meet the needs of the performed analysis. The structural changes will result in a flexible time slice structure. With the flexible time slice structure, the model will be able to perform analyses with any number of time slices. However, there is no intention to perform the analyses with more than 8760 time slices.

Regarding the spatial resolution of TIMES-DK, all sector activities (i.e. processes) are explicitly defined over two regions (Section 2.3). However, within each sector, processes can be further specified at a greater geographical detail. For instance, the residential sector follows a geographical representation based on DH areas while the transport sector splits the modal demands according to the trip distance (without currently taking into account the urbanisation area where the trip takes place). The inconsistency in spatial aggregation across sectors may yield more or less detailed modelling, thus results, depending on the sector. Furthermore, neighbouring countries are not endogenously modelled, but only exogenously represented through trade links. The latter limitation is addressed in the SHIFT project by developing TIMES models of the remaining Nordic countries and linking them with TIMES-DK. This will result in endogenous power prices in neighbouring countries. However, the extension of geographical scope of the model does not fully solve the issue of representation of neighbouring countries through trade links. The issue rather migrates from the Danish borders to the borders of the Danish neighbours and third countries.

Inherently to the energy system optimisation methodology, TIMES-DK assumes a role of the central energy planner who makes decisions on behalf of the average consumer with full information, perfect rationality, aiming at maximising the economic utility of the system. This does not allow capturing in detail all the aspects related to consumer behaviour, which

⁵<http://www.nordicenergy.org/flagship/project-shift/>

play a fundamental role in decision-making processes [81]. For instance, in reality in the transport sector, many attributes are involved in the choice of mode and vehicle such as travelling time or charger availability (for electric vehicles). To overcome this limitation, the ongoing COMETS project⁶ aims at improving the representation of behaviour in the transport sector within bottom-up optimisation energy system models [72, 82]. The representation of behaviour is improved by extending the technology competition within the modes to competition across modes by aggregating the passenger modal travel demands into demand segments based on the distance range.

Finally, TIMES-DK is not yet openly available. This limits its application and usage potential. Moreover, publicly accessible code and data is a prerequisite for transparency, repeatable research, model maintenance and development, verification of results and not least model-based learning [2, 83]. In this view, while TIMES-DK has already been used for projects outside of the institutions that developed it [70], the model should become available to third parties (e.g. consultancy companies, NGOs, university students) to support a democratic process around the needed decisions for the future Danish energy system. Additionally, an open model development would lead to improved data quality, validation of assumptions and correction of errors. After all the data in the model has been attached with an open licence, TIMES-DK will be made publicly available.

6. Conclusion

This paper presents TIMES-DK, the first Danish energy system model that includes the complete national energy system and covers investments over the entire modelling horizon. The development of the model was initiated from a growing need to be able to prioritise and describe socioeconomic optimal pathways to a low-emissions society across all economic sectors. Covering all sectors in a single model speeds up the analysis process, while providing a consistent method of policy evaluation across all the sectors. Another important consideration taken into account in the development of TIMES-DK is that it is based on data sets that are continuously maintained making it easier to update and refine the model.

Thanks to being developed in close collaboration between an energy agency, a university and an SME the model allows for a wide range of applications. They include, but are not limited to, exploratory energy scenarios and various policy analysis. Linking TIMES-DK to the CGE model developed hand-in-hand provides additional insights into, e.g. impact on public finance, burden shifting between sectors or CO₂-leakage from ETS (Emission Trading Scheme) to non-ETS sectors.

TIMES-DK benefits from the continuous development of the TIMES model generator carried out by the ETSAP community, as well as know-hows and insights generated within the community through application of the TIMES models in the various parts of the world.

A continuous model development is essential to ensure that the model remains capable of addressing challenges of the future. Our ongoing projects are contributing to improving the representation of behavioural aspects in TIMES-DK, as well as making temporal dimension

⁶<http://www.cometsproject.dk/>

of the model easily adjustable. At the same time, efforts at ensuring broad availability and usage of the model can facilitate the discussion on the Danish energy transition towards carbon neutrality.

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**REACHING CARBON NEUTRAL
TRANSPORT SECTOR IN DENMARK
– EVIDENCE FROM THE
INCORPORATION OF MODAL SHIFT
INTO THE TIMES ENERGY SYSTEM
MODELING FRAMEWORK**



Reaching carbon neutral transport sector in Denmark – Evidence from the incorporation of modal shift into the TIMES energy system modeling framework

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ABSTRACT

Energy/Economy/Environment/Engineering (E4) models have been rarely apt to represent human behaviour in transportation mode adoption. This paper contributes to the scientific literature by using an E4 model to analyse the long-term decarbonisation of the Danish transport sector. The study is carried out with TIMES-DK, the integrated energy system model of Denmark, which has been expanded in order to endogenously determine modal shares. The methodology extends the technology competition within the modes to competition across modes by aggregating the passenger modal travel demands into demand segments based on the distance range. Modal shift is based not only on the levelised costs of the modes, but also on speed and infrastructure requirement. Constraints derived from the National Travel Survey guarantee consistent travel habits and avoid unrealistic modal shifts. The comparison of model versions with and without modal shift identifies its positive contribution to the fulfilment of the Danish environmental targets. Four sensitivity analyses on the key variables of modal shift assess how their alternative realizations affect the decarbonisation of the transport sector and enable shifting away from car. The results indicate that less strict travel time budget (TTB) and increased speed of public bus lead to a more efficient decarbonisation by 2050.

1. Introduction

Transport is a fundamental driver of economy and society and it plays a primary role in supporting economic growth and quality of life. Nonetheless, transport is also responsible for many externalities at local, regional and global levels. At the local scale, transport is responsible for accidents, road damage, vibration, noise and congestion (Santos et al., 2010). At the regional scale, transport is responsible for emitting several air pollutants affecting human health. A widely discussed global externality is transport's contribution to climate change. Since 1970 greenhouse gas (GHG) emissions from the transport sector have more than doubled, increasing at the fastest rate among all the end-use energy sectors (Sims et al., 2014). In 2010, transport accounted for approximately 23% of energy-related CO₂ emissions worldwide (International Energy Agency, 2009) and about 36% in Denmark (Nordic Energy Research and International Energy Agency, 2016). So far, the efforts to reduce transport GHG emissions by improving powertrain efficiency and fuel standards have been offset by the increase of transport activity. Moreover, alternative fuelled vehicles (AFV) still require policy support to gain a significant market share (Mulholland

et al., In preparation). An evidence is that the derogation of the vehicle registration tax (VRT) towards electric vehicles (EVs) in Denmark has seen a fall in their sale in 2016 (European Environmental Agency, 2017). Besides, the International Energy Agency (IEA) (2009) estimates that 2050 worldwide car ownership could triple, while freight transport by truck and aviation could increase four-fold, thus leading to a doubling of energy use in transport. In order to reverse this tremendous trend, the IEA proposes a combination of both technological and behavioural measures: *avoid*, *shift*, *improve* and *switch* (International Energy Agency, 2012). *Avoid* entails mitigating the mobility demands by, for instance, densifying the urban structure, teleworking and virtual mobility. *Shift* consists in increasing the market shares of low-carbon modes, fostered by e.g. improving the level of service (LoS) of public transport and deploying biking infrastructure. *Improve* focuses on enhancing the vehicle efficiency by decreasing its weight, increasing the occupancy and load factor and developing advanced engines. *Switch* consists in substituting oil-based fuels with low-carbon fuels.

In this paper, we investigate transport-related issues through the lens of an E4 optimization model, specifically a TIMES/MARKAL model. Such energy system models are valuable tools for long-term

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energy planning. Decision makers have been using them to perform policy analyses and to determine least-cost pathways toward low CO₂ energy systems considering cross-sectoral dynamics and synergies. TIMES models are described as technology rich, because effectively representing the techno-economic dimensions of an energy system. However, TIMES models are still poor at representing consumers' behaviour (Schäfer, 2012; Waisman et al., 2013; Cayla et al., 2011; Venturini et al., *In preparation*). Therefore, it is necessary to improve the representation of transport behaviour in TIMES and similar bottom-up (BU) E4 models to validate their application in transport policy analysis. For this purpose, this study develops a methodology that integrates endogenous modal shift into BU E4 models to analyse its potential contribution to the decarbonisation of the Danish transport sector. The approach is fully implemented and tested in the TIMES model of the Danish energy system, TIMES-DK (Balyk et al., *In preparation*).

This paper reviews how modal choice has been represented previously in transport and energy system models in Section 2. Then, in Section 3 an overview of the TIMES model generator is provided, followed by a detailed description of the methodology that enables endogenous modal shift. In Section 4 the novel approach is used to assess the benefits of modal shift in reaching a carbon-neutral transport sector, by comparing the results of two versions of TIMES-DK, one without and one with modal shift integrated. Then, four sensitivity analyses are conducted on the key variables of modal shift to assess how their different realizations affect the energy system and enable shifting away from car. Moreover, the most interesting outcomes of the study are used to suggest energy policies promoting modal shift. Section 5 discusses the main shortcomings of the model developed and recommends the direction of future research for improving the representation of transport behaviour in BU E4 models. Finally, Section 6 presents the conclusions.

2. Modal choice in energy and transport models

Modal shift implies a transfer of demand from one mode to another. The dynamics of modal shift result from modal choice changes, corresponding to an evolution in users' preferences. In turn, users' preferences are reshaped due to changes in socioeconomic status, subjective opinion, modal characteristics, infrastructure and policy.

Transport models are long-established tools for simulating modal choice. Their structure is composed of four steps: trip generation, trip distribution, modal choice and route assignment. In the third step, modal shares are determined via a multinomial logit model (MNL) or a nested multinomial logit model (NMNL). The MNL and NMNL models are based on a large number of attributes that describe the LoS of the alternative modes and the socioeconomic characteristics of the population. Thanks to their highly disaggregated population description and their ability to base decisions on many attributes, transport models depict realistically households' modal choice, thus being a reliable tool to assess modal shift. However, the benefits of transport models cannot be directly replicated in linear optimization models due to incompatibilities between the two modeling frameworks. In fact, the MNL mathematical formulation of transport models based on exponential functions cannot be incorporated in linear optimization models. In the field of E4 models, the contribution of modal shift to CO₂ mitigation was initially evaluated through "what-if" analyses, which assess the effect of exogenously assumed levels of shift on the energy system and environment (International Energy Agency, 2009; GEA writing team, 2012). Lately, research interest is focusing on the endogenisation of modal choice (Venturini et al., *In preparation*). Thanks to the inclusion of simulation methods in the model structure, top-down (TD) (Karplus et al., 2013) and hybrid (H) (Pietzcker et al., 2010; Horne et al., 2005) E4 models are able to simulate modal choice through constant elasticities of substitution (CES) and MNL functions, which have been used for this purpose for more than four decades, thus being very reliable.

Bottom-up optimization energy system models lag behind TD and H models concerning their ability to represent modal shift: the portfolio of technologies is endogenously determined only accounting for techno-economic parameters, e.g. capital costs, operation and maintenance (O&M) costs and fuel costs. CES and MNL functions do not directly fit in the optimization framework and thus for this class of models the research on new modeling techniques for representing modal choice is a cutting-edge topic. For BU optimization E4 models, a recent literature review (Venturini et al., *In preparation*) recognizes two main approaches to incorporate behaviourally realistic modal choice. One consists in linking the BU energy system model with an external transport simulation model that integrates the behavioural features and determines modal shares (E3MLab, 2014; Girod et al., 2012; Brand et al., 2012; McCollum et al., 2016). In the other approach, modal shift is assessed endogenously in the energy system model, by enlarging the traditional model structure to accommodate some transport-specific variables, such as TTB and transport infrastructure (Daly et al., 2014; Pye and Daly, 2015). While the latter method poses some limitations on the level of disaggregation and on the amount of model attributes, the benefits of representing modal shift directly within an energy system model are multifold. First, it enables assessing a much wider variety of policies directly within the energy system model. Then, it allows to analyse transport with an energy system-wide perspective, thus supporting the understanding of the reciprocal implications of decisions taken in the transport and energy systems. The analyses performed in this paper utilize a methodology belonging to the second category of the taxonomy described above.

3. Methodology

This section describes the methodology for incorporating modal shift in TIMES-DK. The approach develops upon previous works by Daly et al. (2014) and Pye and Daly, (2015), as explained in detail in Section 5. This process forgoes changing the core modeling paradigm, only altering the conventional model structure (described in Section 3.1). Modal shift is based not only on the levelised costs of the modes, but also on new parameters, namely speed and infrastructure requirements. Moreover, some constraints derived from a National Travel Survey spatially consistent with the scope of analysis avoid unrealistic modal shifts in the model. Within the scope of this study, the soft variables influencing modal choice (Tattini et al., *In preparation*) have been neglected, and modal shift is endogenously determined via a suitably constrained socioeconomic optimization.

The methodology is developed within TIMES-DK, the TIMES model that represents the entire Danish energy system, from primary energy supply, through energy conversion, until transport, industry, residential and commercial end-use sectors (Balyk et al., *In preparation*). The transport sector in TIMES-DK includes the explicit representation of passenger and freight transport, both split in aviation, maritime and inland. In particular, inland passenger transport includes private car, bus, coach, rail (metro, train, S-train), 2-wheeler (motorcycle and moped) and non-motorized (bike and walk). Regarding time granularity, the transport sector is described at annual level, i.e. the model does not characterise intra-annual and intra-day variations. The new version of TIMES-DK that incorporates endogenous modal shift hereby presented is called TIMES-DKMS. In TIMES-DKMS, modal shift is limited to inland passenger transport. For national trips, ships and airplanes do not compete with inland modes due to Denmark's small land surface area. Each mode competes with all others to increase its market share, being fixed the total travel demand. The car mode is an exception: its mobility demand can be replaced by any mode, but its maximum value in 2050 is limited to the baseline projection in TIMES-DK. This is due to the fact that the analyses in Section 4 focus on the long-term potential shift away from car.

Before describing the methodology in detail (Sections 3.2–3.6), Section 3.1 describes TIMES modeling framework and then compares

the structures of the passenger transport sector of TIMES-DK and TIMES-DKMS.

3.1. Overview of the transport sector TIMES before and after integrating modal shift

The Integrated MARKAL-EFOM System (TIMES) is a model generator developed and maintained by the Energy Technology Systems Analysis Program (ETSAP), a technology collaboration program of the IEA (Loulou et al., 2016). TIMES is based on the bottom-up approach and thus is referred to as “technology explicit”. More specifically, TIMES is a techno-economic partial equilibrium model generator assuming perfect competition. TIMES models are linear optimization problems and the solution is calculated as the minimization of the sum of the total system costs discounted to a reference year, subject to user-defined technological, environmental, resource availability and policy restrictions. It is used by decision makers for performing long-term energy system analyses, for assessing energy sector dynamics and for seeking the least-cost pathways to meet future energy service demands while complying with environmental targets (Bahn et al., 2013; McCollum et al., 2012). A detailed description of TIMES is provided by (Loulou et al., 2016).

Focusing on the passenger transport sector in TIMES, Fig. 1 provides a schematic representation of the structure of the passenger transportation sector in TIMES-DK model. Exogenous travel service demands (expressed in million passenger-km) are defined for each mode, from the base year until the end of the time horizon. Many technologies compete to meet every exogenous travel demand. However, technologies can only complete intra-modally. Competition between technologies is exclusively based on costs: TIMES seeks to meet the modal transport demands with the portfolio of technologies characterized by the lowest operational and capital costs, while complying with the constraints. The techno-economic parameters characterising the technologies are set exogenously to the model and change over time, while fuel costs are determined endogenously and simultaneously via the optimization.

The proposed structure of the passenger transport sector of TIMES-DKMS, enabling endogenous modal shift, is represented in Fig. 2. On

the right side are the aggregated mobility demand commodities, which can be fulfilled by several modes (see Section 3.3). To fulfil the travel demands the modes do not consume just fuels, but require in input also infrastructure and time commodities. The latter is limited by the TTB process (see Section 3.3). The infrastructure commodities are provided by two types of technologies, one representing the existing infrastructures, another those newly available for expansion. The technologies representing the existing infrastructures have capacity bounds that limit the amount of extra travel demand that can be accommodated (see Section 3.4). As the demand fulfilled by the modes equals the capacity bounds of the infrastructure technologies, saturation occurs. The extra infrastructures required must then be provided by the “new infrastructure” technologies, which involve a cost for the system. Being the structure of the model re-organized as in Fig. 2, some additional constraints based on the observations of a travel survey are required to ensure realistic modal shift (see Sections 3.5 and 3.6).

3.2. Aggregation of mobility demand

In order to introduce competition across modes and thus modal shift, all the mode-specific mobility demands are aggregated into four distance-specific overall travel demands, namely extra-short (XS), short (S), medium (M) and long (L), as done by Daly et al. (2014). With this structure the newly aggregated mobility demands can be satisfied by different modes, as visible on Fig. 2. The ability for a mode to fulfil a certain range-specific demand is based on the driving patterns, which state the percentages travelled in the different distance ranges, as visible in Table 1 (processed from the Danish National Travel Survey (TU survey) (Transport DTU, 2016)). The aggregated demands are then projected until the end of the time horizon (year 2050), considering the mode-specific demand projections from Landstrafikmodellen (LTM), the transport simulation model for Denmark (Transport DTU, 2017).

3.3. Travel time budget

The rationale of the adoption of the travel time budget (TTB) has been provided by (Schäfer and Victor, 2000), which claims that across different societies, historical periods, geographical areas and income

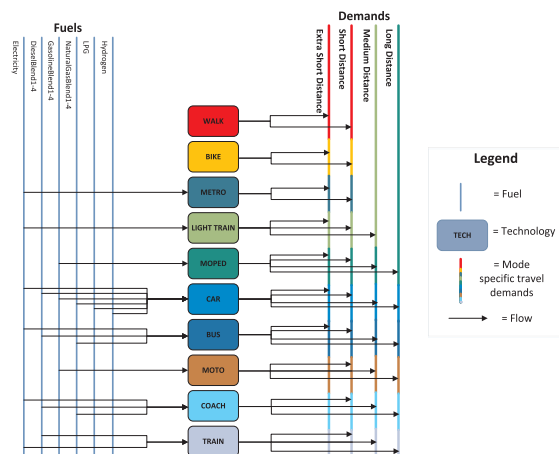


Fig. 1. Ordinary structure of the passenger transport sector in TIMES-DK.

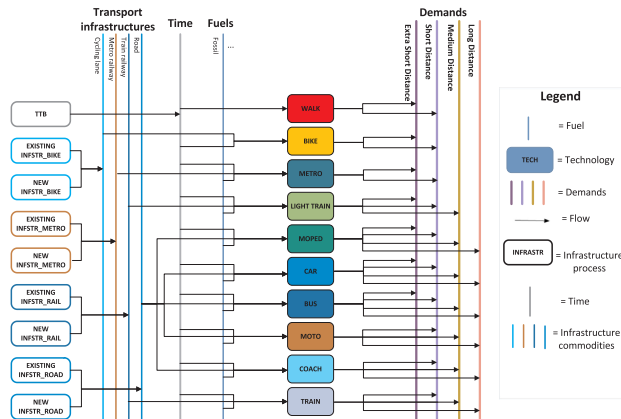


Fig. 2. Proposed structure of the passenger transport sector in TIMES-DKMS for incorporating modal shift.

Table 1
Driving patterns for the modes of TIMES-DK (personal elaboration based on TU Survey, Transport DTU).

	Extra Short (< 5 km)	Short (5–25 km)	Medium (25–50 km)	Long (> 50 km)
Car	6%	30%	22%	42%
Battery electric car	10%	40%	40%	10%
Public bus	19%	56%	16%	9%
Coach	0%	10%	10%	80%
Motorbike	0%	34%	27%	39%
Moped	20%	67%	9%	4%
S-train	7%	60%	33%	0%
Train	0%	9%	20%	71%
Metro	37%	63%	0%	0%
Bike	58%	42%	0%	0%
Walk	93%	7%	0%	0%

Table 2
Modal speed by trip distance [km/h] (personal elaboration based on TU Survey, Transport DTU).

	Extra Short (< 5 km)	Short (5–25 km)	Medium (25–50 km)	Long (> 50 km)
Car	30	48	63	78
Public bus	21	31	47	65
Coach		37	59	71
Motorbike		45	64	73
Moped	27	38	41	60
S-train	36	45	55	
Train		61	71	91
Metro	32	40		
Bike	16	18		
El-Bike	18	19	20	
Walk	6	6		

classes people spend the same amount of time per day traveling. In this methodology, the TTB at the same time avoids that the new aggregated demands are satisfied only according to cost-optimal criteria and ensures consistency with historically observed travel time. The incorporation of TTB requires to introduce a new parameter: speed. Speed is constant across all the technologies belonging to the same mode (with

the exception of electric and normal bikes). Speeds are range-specific, which means that the same mode has different speeds depending on the trip distance class, as shown in Table 2.

Speeds are obtained from TU Survey as the average of the ratios between the trip distance and the trip travel time, weighted on the session weights (the weights associated to each observation that enable to scale up the population surveyed to the real population). Eq. (1) describes the calculation:

$$Speed_m = \frac{\sum_{i=1}^n \frac{TL_i \cdot w_i}{TT}}{\sum_{i=1}^n w_i} \quad (1)$$

where m is the mode, i corresponds to i -th observation, n is the total number of trips registered in TU Survey per mode m , TL is the trip length, TT is the trip travel time and w is the session weight (which sum is different from 1).

TU Survey determined for year 2010 (the base year of TIMES-DK) an average per capita daily TTB of 54.8 min (Transport DTU, 2016), which corresponds to 1588 million-hours for the overall Danish transportation sector. However, such quantity was calculated taking into account a wider portfolio of modes than in TIMES-DK and thus is not fully consistent with its scope. With defined speeds and mobility demands, the TTB for the base year 2010 is provided as an output of TIMES-DK by dividing modal travel demands by modal speeds. Its value is 1573 Million-hours, very similar to the one empirically observed by TU Survey considering a wider set of modes. The TTB has then been projected until 2050 using Eq. (2):

$$TTB_y = TTB_{2010} \cdot P_{g_y} \quad (2)$$

where y is the year, TTB_{2010} is the travel time budget in the base year and P_{g_y} is a driver representing the estimate for Danish population growth in year y with respect to 2010. The TTB in the future years is provided in Table 3.

3.4. Infrastructure requirements

Transport infrastructure is a key driver of mobility demand and modal choice (Schwanen et al., 2011; Moeckel et al., 2014). Transport simulation models account for the capacity of the road network and its effect on travel time and modal generalized costs (Rich, 2015). Instead, transport infrastructure is rarely represented in energy systems models.

Table 3
Projection of the travel time budget for the Danish transportation sector until 2050 [million hours].

Year	Denmark East	Denmark West
2010	693	880
2015	714	906
2020	734	931
2030	744	943
2040	756	960
2050	756	960

The rationale for incorporating transport infrastructure in TIMES is that there must always be enough infrastructure capacity to accommodate the mobility demand. The existing infrastructure is enough for the current levels of mobility demand, but in order to accommodate future travel demand, after infrastructures saturate, investments in additional network capacity are required. Therefore, infrastructure requirements limit modal shift, as a considerable shift between modes may end up in infrastructure saturation, subsequently requiring additional infrastructure capacity, which implies a remarkable cost.

Five infrastructures are included in TIMES-DKMS: road (shared by cars, 2-wheelers, buses and coaches), bike lane and three different railways for train, S-trains and metro. The transport infrastructures are not represented explicitly in the model, but as commodities that the modes consume in order to fulfil the mobility demand, as shown in Fig. 2. The existing infrastructure commodities are limited and when they saturate the model endogenously invests in new ones (with a cost associated) in order to fulfil the extra demand. The availability of existing infrastructures to accommodate extra mobility with respect to the base year depends on their capacity utilization levels. The capacity utilization levels are calculated by comparing the maximum traffic volume with the infrastructure capacity (The Danish Road Directorate, 2015; Den Boer et al., 2011), as described in Eq. (3).

$$\text{Infrastructure capacity utilization level} = \frac{\text{Maximum vehicle flow}}{\text{Infrastructure capacity}} \quad (3)$$

The road capacity (defined as maximum vehicles/hour though a given point) is calculated as indicated by the The Danish Road Directorate (2015), considering road type (motorways or municipal roads) and design (number of lanes). The peak-hour flow of road vehicles (vehicles/h) is provided by Statistics Denmark (2016). The railway capacity (expressed in train-km) depends on the length of single-track and double-track ways (Den Boer et al., 2011). Train traffic (train-km) accounts for both passenger and freight trains (Statistics Denmark, 2016). The maximum utilization levels of the Danish transport infrastructures are described in Table 4. It is important to notice that these values are aggregated at national and annual level. Therefore their use should be limited to broad energy system analyses, while for specific transport studies it is recommended to lead more geographically and temporally detailed assessments.

The cost of the existing infrastructure is not included in the system cost, because it can only be extended, not abandoned nor replaced by a different one. On the other hand, new infrastructures have both an investment and an O&M cost. Infrastructure costs have been calculated from historical expenditures of expanding, and maintaining the

Table 4
Capacity utilization level for the transport infrastructures in peak-hour.

Transport Infrastructure	Capacity utilization level
Road Infrastructure	81%
Bike Infrastructure	90%
Train Infrastructure	91%
S-train Infrastructure	87%
Metro Infrastructure	79%

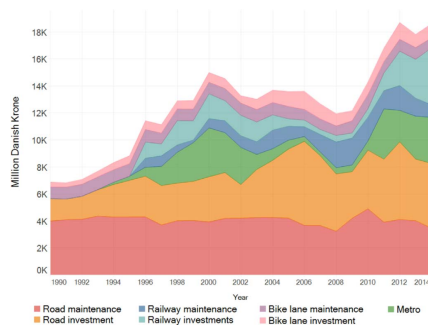


Fig. 3. Cumulated investment and maintenance costs for different transport infrastructures between 1990 and 2014 in Denmark (MDKK/year).

transport networks (The Danish Road Directorate, 2016a, b) and from the increase of mobility demand ΔMpk_m within the same time period (Statistics Denmark, 2016), as shown in Eqs. (4) and (5).

$$\text{Infrastructure cost}_{IV} = \sum_y \frac{\text{Investments}_y}{\Delta Mpk_m} \quad (4)$$

$$\text{Infrastructure cost}_{O\&M} = \sum_y \frac{O\&M\text{costs}_y}{\Delta Mpk_m} \quad (5)$$

The cumulated historical investment and O&M costs for the different transport infrastructures from 1990 to 2014 are shown in Fig. 3. The total infrastructure costs for road and railway, which are shared by passenger and freight transport, have been split between the two forms of transport. For road infrastructure the total cost is allocated on the basis of the contribution to pavement wear, considering the weight of the passenger and freight vehicle stock (Statistics Denmark, 2016). For the railway infrastructure the total cost is allocated on the basis of network use, considering the volume flows (in train-km) of passenger and freight transport (Statistics Denmark, 2016). For all the modes represented in TIMES-DK the levelized cost, calculated as the sum of vehicle cost (capital + O&M), fuel cost and infrastructure cost, is shown in Fig. 4. It is worth noticing that road infrastructure is shared by several modes and therefore the investment in road network can be used by one mode in one year and by a different one the following years if modal shift occurs.

3.5. Maximal and minimal modal shares

The review of scientific literature did not reveal any methodology to

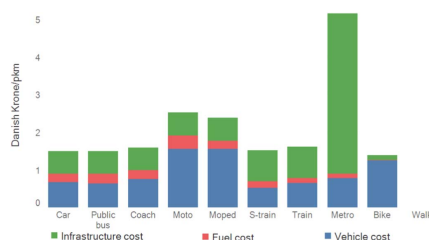


Fig. 4. Levelized cost per mode with infrastructure in 2035.

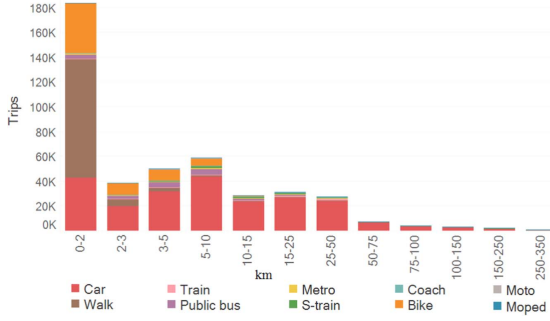


Fig. 5. Trip distance profile for Denmark. Based on (Danish National Travel Survey, Transport DTU 2006-16).

estimate the maximum modal shift potential in passenger transport, which is case specific. The model proposed avoids unrealistic future modal shares by imposing a set of constraints that limit the modal competition to distance ranges realistically covered by the modes. In particular, modal competition is regulated so that mode A can fulfil the mobility demand in a certain distance range previously satisfied by mode B, only if both A and B cover that same distance range. The realistic distance ranges per mode are registered in the trip distance profile, which classifies the number of trips per mode and distance classes. For this case study of Denmark, the trip distance profile is the one observed by TU Survey, shown in Fig. 5.

Maximal modal shares in 2050 are incorporated in the model as a set of constraints limiting the amount of demand in each distance range (XS, S, M and L) that the modes can fulfil. The expression for calculating the maximal modal share of a mode in a distance-range is provided in Eq. (6): it is the sum of the baseline modal demand projection for 2050 and the maximal modal shift towards that mode from all the competing ones. Moreover, the maximal modal shift from a mode to the sum of all others must be lower than the baseline demand of that mode in 2050, as stated in Eq. (7).

$$\text{Maximalmodalshare}_{2050,m,d} = \text{Demand}_{2050,m,d} + \sum_{j=1}^M \text{Replace}_{m,j,d} \quad \forall m, j, d \quad (6)$$

$$\sum_{j=1}^M \text{Replace}_{j,m,d} \leq \text{Demand}_{2050,m,d} \quad \forall m, j, d \quad (7)$$

Where m is the mode, j is an index corresponding to the j -th mode (different than m), M is the total number of modes in the model, d is the distance range, Demand_{2050} is the baseline mobility demand projected to 2050 (without modal shift) and Replace is the mobility demand that can be replaced.

The minimal modal shares are set for non-motorized modes, 2-wheelers and public transport in 2050. For non-motorized modes and 2-wheelers, the minimum modal shares have been obtained examining the purposes of the trips in TU Survey. For transit the minimum modal shares are obtained from TU Survey considering the number of people without access to car. People who do not own nor have access to a car can use non-motorized modes for short distance trips, but for medium and long distances public transport is needed, as reflected in Fig. 5. The minimum modal shares are based on the assumption that traveling habit, trip purpose and car access observed in TU Survey are valid also for the future.

3.6. Maximum rate of modal shift

The maximum rate of modal shift avoids overly fast shifts. Being the transportation sector characterized by an existing vehicle stock that changes slowly and that relies on long-lasting infrastructures with sunk costs, shift is likely to happen at slow pace. Eq. (8) describes the constraint for the maximum rate of shift:

$$\Delta MS_{m,y} \leq r_m \quad \forall m, y \quad (8)$$

The variation in the market share ΔMS of mode m between years y is limited by the rate of modal shift r , which is based on linear interpolation between the modal share in the base year and the maximal and minimal modal share in 2050 calculated with Eq. (6) (Pye and Daly, 2015).

4. Results

This section explores the effect of integrating passenger modal shift into the TIMES energy system model of Denmark. First, Section 4.1 analyses the potential role of modal shift for fulfilling the Danish environmental targets. Then, in Section 4.2 four sensitivity analyses on the key variables of modal shift are conducted in order to assess how alternative possible realizations of such variables affect the energy system and enable shifting away from car. Finally, Section 4.3 informs policy makers of the potential implications of the applied method and recommends energy policies based on the results of the study.

4.1. Modal shift contribution to the Danish environmental targets

Both the IEA and the European Commission regard modal shift as one of the key measures to reach a future resource-efficient and low-carbon transport system (International Energy Agency, 2012; European Commission, 2011). The potential benefit of modal shift for decarbonising the Danish transport sector is hereby assessed by comparing the results of two versions of the TIMES model of Denmark: one without modal shift (the standard version of TIMES-DK), another with modal shift integrated (TIMES-DKMS, described in Section 3). TIMES-DK and TIMES-DKMS have the same underlying data set describing the techno-economic parameters of the transport technologies (Energistyrelsen, 2016). Moreover, both models' results are consistent with the Danish environmental targets: minimum 50% of total annual electricity production from wind by 2035, fossil-free power and heat generation by 2035 and no consumption of fossil fuels in the entire energy system by 2050 (The Danish Government, 2016). For TIMES-DK the solution is found only seeking the least-cost portfolios of vehicles to fulfil the exogenously provided modal demands. On the other hand, TIMES-

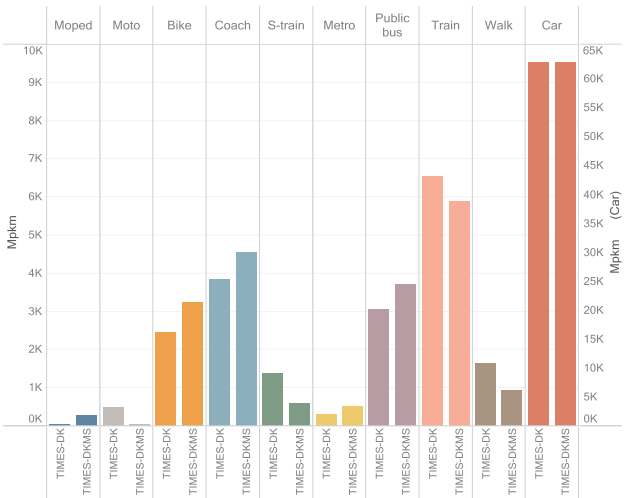


Fig. 6. Comparison of the modal shares in 2050 for TIMES-DK and TIMES-DKMS.

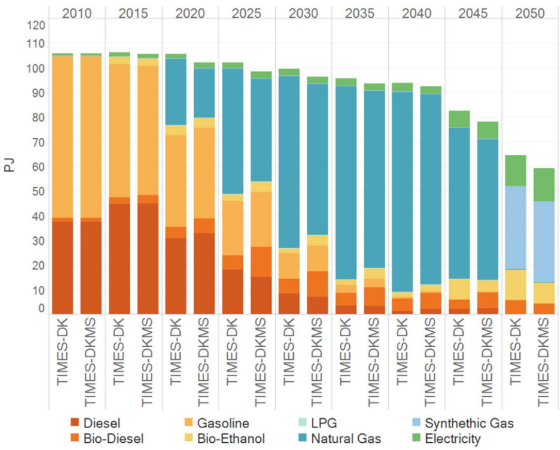


Fig. 7. Comparison of the fuel consumed by inland passenger transport sector in TIMES-DK and TIMES-DKMS.

DKMS determines the solution as a co-optimization of the modal shares and vehicle shares. The modal shift option provides TIMES-DKMS additional flexibility, since it can meet the environmental targets by increasing the market shares of some modes at the expense of other ones. The modal shares for the two models in 2050 are compared in Fig. 6. TIMES-DKMS determines such new optimal modal shares not only on a least-cost basis, but considering also speeds and infrastructure availability, while respecting the TTB, the travel patterns, the maximal and minimal modal shares and the maximum shift rate.

In 2050 in TIMES-DKMS bike, bus, coach, moped and metro

increase their market share with respect to TIMES-DK, at the expense of moto, train, S-train and walk. Since the increase of car is limited and public bus and coach have the lowest levelised cost among the modes using road, the latter two modes increase the market share, but without saturating road infrastructure. Motorbike is more expensive than the other options using road (as shown on Fig. 4) and therefore its demand decreases, being replaced mainly by coach for long distance and by public bus for short distance. The demand for train-based travel reduces with respect to TIMES-DK, to avoid its infrastructure cost, and is mainly replaced by coach, which has a similar driving pattern. The driving

pattern of S-train is oriented towards short distance and does not enable it to take over the demand shifted away from moto and train, which is mostly long-range. Therefore, the market share of S-train decreases and is mainly substituted by public bus, which has a similar driving pattern but covers also longer distances, and by moped, more expensive but that avoids incurring infrastructure costs. As the average modal speed in long-range decreases with respect to TIMES-DK, the model decreases the modal share of walk, characterized by zero costs but with very low speed, and replaces it with faster yet more expensive modes, namely bike and metro. These dynamics highlight that the key variables affecting modal shift in this study are modal speeds, TTB and driving patterns. The combination of the first two ensures the competitiveness of faster yet more expensive modes in a cost-optimization modeling framework and ensures that the modal mix has high enough speed. The latter regulates modal competition within each distance range, ensuring that the modes fulfil the travel demand only in the feasible distance ranges (see Table 1).

The variation of modal shares in Fig. 6 affects the fuel consumption of inland passenger transport sector, as visible from Fig. 7. The fuel consumption patterns of TIMES-DK and TIMES-DKMS have similar trends. In both models the consumption of diesel-blended fuel (obtained blending diesel and bio-diesel) initially increases and then reduces in the long-term. The share of bio-diesel in the blend gradually increases until reaching 100% in 2050. The consumption of gasoline-blended fuel (obtained blending gasoline and bio-ethanol) decreases over time, while the share of bio-ethanol in the blend increases until 100% in 2045. Moreover, electricity and gas become the main components of the future fuel mix. Overall, in both models the transport sector in 2050 consumes only fossil-free fuels: bio-fuels and synthetic gas obtained processing biomass, and electricity generated from carbon-neutral sources. Beside these similar patterns between TIMES-DK and TIMES-DKMS, the latter model in 2050 is characterized by a lower total fuel consumption (about – 8.2%) and by greater penetration of electricity (about +9.4%). Moreover, the decarbonisation of the inland passenger transport sector in TIMES-DKMS occurs at faster pace, as visible comparing the trends of the energy intensity of the two models in Fig. 8. In turn, the energy intensities are reflected in the CO₂ emissions, which in TIMES-DKMS decrease at faster rate, as shown in Fig. 9. The decarbonisation pathway recommended by TIMES-DKMS is characterized by about 1.9% lower cumulative CO₂ emissions from the whole energy system in the time horizon 2010–2050 with respect to TIMES-DK. Such additional cut in emissions is mainly attributable to the transport sector, characterized by about 5.2% lower cumulative CO₂ emissions in TIMES-DKMS, as visible in Fig. 9. Moreover, the introduction of modal shift in the model framework enables to identify more cost-effective pathways to reach carbon neutrality. For this case study of Denmark, the solution found by TIMES-DKMS is characterized by a reduction of total system cost over the modeling period 2010–2050 of about 1.5% with respect to that of TIMES-DK, as visible in Fig. 10. Overall, the optimal modal shift identified in TIMES-DKMS allows to decarbonise the Danish transport sector at faster pace, with lower overall CO₂ emissions and at a lower cost for the society.

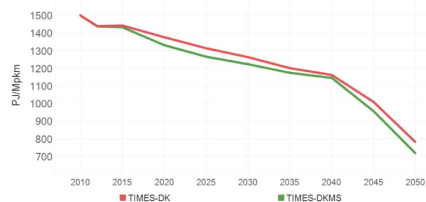


Fig. 8. Trend of the energy intensity of inland passenger transport sector in Denmark.

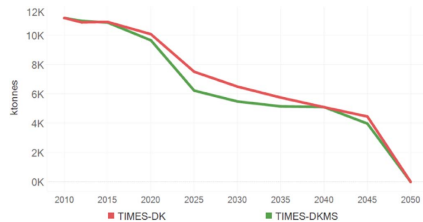


Fig. 9. Trend of CO₂ emissions from the Danish inland transport sector.

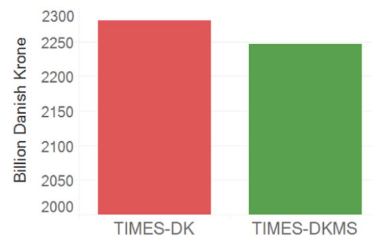


Fig. 10. Comparison of the cost of the entire energy system throughout the modeling period 2010–2050 in the carbon-neutral scenario for TIMES-DK and TIMES-DKMS.

4.2. Sensitivity analyses

After having assessed the potential contribution of modal shift to the decarbonisation of the Danish energy system, this section analyses how different outcomes of the key variables of modal shift identified in Section 4.1 can influence the Danish energy system and can enable shifting away from car. With this purpose, four sensitivity analyses are carried out, assessing the influence on modal shares, car stock and fuel consumption. All the sensitivity analyses are performed on TIMES-DKMS and are consistent with the Danish environmental goals (The Danish Government, 2016). The key variables changed with respect to the reference scenario *Ref* are: travel time budget, driving patterns and speed. An overview of the sensitivity actions is provided in Table 5.

4.2.1. Increase of Travel Time Budget (High TTB)

There have been many proponents of the concept of constant travel time budget, many studies that did not find any evidence and others that suggested an annual increase of TTB (Stopher and Zhang, 2003). Moreover, some game changers like driverless cars and behavioural changes, such as working while traveling, could lead to an increase of the time dedicated to traveling (Malokin et al., In preparation). This

Table 5
Description of scenarios for the sensitivity analysis.

Scenario	Description
<i>Ref</i>	Reference scenario for TIMES-DKMS. Details of the model provided in Section 3, consistency with the Danish environmental goals
<i>High TTB</i>	TTB 10% higher than in <i>Ref</i>
<i>Flex DP</i>	Flexibility of $\pm 20\%$ regarding the driving patterns compared to <i>Ref</i>
<i>High Speed Bus</i>	Speed of bus in extra-short, short and medium distance 10% higher than in <i>Ref</i>
<i>High TTB & Flex DP</i>	Combination of <i>High TTB</i> scenario and <i>Flex DP</i> scenario

sensitivity analysis assesses the effect on the Danish energy system of a 10% increase of TTB. Such case corresponds to a society willing to dedicate more time to mobility and that prefers slower but cheaper transport.

4.2.2. Flexible driving patterns (Flex DP)

Driving patterns state what percentages of the total vehicle-kilometres are travelled in the four distance-range categories. In *Ref* scenario, the driving patterns are those registered by TU shown in Table 1 and are constant throughout all the time horizon. Nonetheless, in the long-term the use of transport technologies can vary with respect to historical observations, as an effect of policies, regulations, infrastructure deployment, behavioural changes and technology development. This analysis assumes $\pm 20\%$ flexibility of driving patterns with respect to the standard values in *Ref*. In this way the model has two degrees of freedom: it can shift the demand between modes and also rearrange the driving patterns so that the modes better complement each other.

4.2.3. Increase of the speed of bus mode (High Speed Bus)

This analysis evaluates the effect of an increase of 10% of the speed of public bus in extra-short, short and medium distance. In particular, the speed changed is that of public bus because of its similarities with car and thus the potentiality to replace it. In fact, both public bus and car use road infrastructure, they have similar levelised costs and both cover all the distance-ranges, even if bus with lower speed.

4.2.4. Combination of increase of TTB and flexible driving patterns (High TTB & Flex DP)

This analysis evaluates the behaviour of the Danish energy system and the variation of car usage in case of a simultaneous increase of travel time budget and greater flexibility in the driving patterns.

Modal shares in *Ref* scenario are depicted for the entire modeling period in Fig. 11, while the changes of modal shares obtained as an effect of sensitivity actions are given in Fig. 12. The highest shift away from car occurs in *High TTB* scenario, where mainly public bus and coach take over about 14% of car demand. This outcome suggests that a precondition to reduce the use of car is the acceptance of spending more time traveling. Moreover, in this scenario the market share of metro is almost halved with respect to *Ref*. This confirms that TIMES-DKMS in the *Ref* scenario invests in metro primarily to benefit from its high speed in short distance for fulfilling the stricter TTB. In *Flex DP* scenario modal shares are the most similar to *Ref* and the shift away from cars is the lowest across the scenarios analysed. The reason is that the driving pattern of battery electric vehicles (BEV) re-arranges towards longer distance, making them a cheap solution also for this trip length. Therefore, BEVs become a preferable alternative than other modes, limiting the shift away from cars. It is necessary to simultaneously increase the TTB to appreciate in *High TTB & Flex DP* the highest level of modal shift and a substantial shift away from car. This scenario is also characterized by a substantial increase of walking, which adjusts the driving pattern towards short distance, thus replacing part of the market share of bike. However, it is important to note that the model

does not assume any infrastructure cost for walk, which requires further research to be evaluated. By increasing the share in long distance, S-train replaces the mobility demand of public bus, 2-wheelers and train. *High Speed Bus* scenario reveals that increasing public bus speed is an effective lever for shifting away from car. In this scenario, together with public bus, the other modes replacing car are coach and S-train. Overall, in the sensitivity analyses performed, the travel demand shifted away from car is mainly replaced by public bus, coach, S-train and walk. Nonetheless, car continues having the greatest modal share by far. Therefore, it is interesting to analyse the response of the car stock to the different sensitivity analyses, which is shown in Fig. 13. Diesel internal combustion engines (ICE) disappear from the car stock already in 2045 in all the scenarios. Gasoline cars reduce their market share, especially after 2020, and consume only bio-ethanol in 2050, as shown in Fig. 14. All the sensitivity analyses identify flex-fuel vehicles (FFV) and mostly gas ICE as transition technologies in the car sector. Moreover, a noticeable increase of electricity and gas powered cars occurs in all scenarios, due to the reduction of costs assumed from the cost projections made by Energistyrelsen (2016). In particular, BEVs become a substantial part of the stock only in the scenarios including flexible driving patterns. As anticipated, the reason is that *Flex DP* scenarios can adjust the driving patterns of the BEVs, which increase the amount of km driven in longer distance (International Energy Agency, 2017). Since all the sensitivity analyses performed fulfil the carbon-neutrality requirement, the fuel mix in 2050 is completely fossil-free. Fig. 14 shows the evolution over time of the total fuel consumption from inland passenger transport sector across scenarios. The total fuel consumption over time decreases in all the scenarios, even if with different paces and leading to different final fuel shares and different total consumptions. The lowest consumption of fuel in 2050 occurs in *High Speed Bus* scenario, thanks to the shift away from car towards more efficient modes and thanks to the significant electrification of the car stock. On the other hand, *Flex DP* is the scenario characterized by the highest fuel consumption in 2050, even higher than in *Ref* scenario. The reason is mainly attributable to a reduced share of low-energy modes (bike, train, public bus and metro), together with a lower shift away from cars towards more efficient modes. Moreover, such large car stock is characterized by a limited electrification (see Fig. 13), resulting in an overall higher energy intensity of the car stock with respect to the other scenarios analysed. The fuel consumption pattern in the different scenarios closely matches the pattern of the types of vehicles in the car stock, due to the fact that car continues being the main mode of transport. Bio-diesel continues to be used in 2050 only by coach and public bus. Hydrogen does not seem a convenient fuel in any of the sensitivity cases assessed.

4.3. Policy implications

The analyses carried out in the previous sections are meant to inform Danish policy makers dealing with energy and transport planning on the benefits of modal shift and to suggest which policy levers should be put in practice in order to decarbonise the transport and energy system in the most efficient way. The study proves that modal shift has

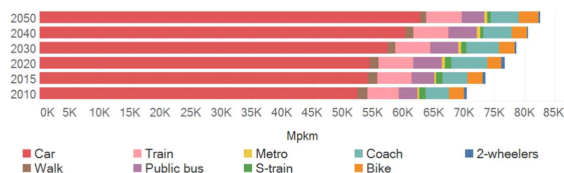


Fig. 11. Modal shares in *Ref* scenario.

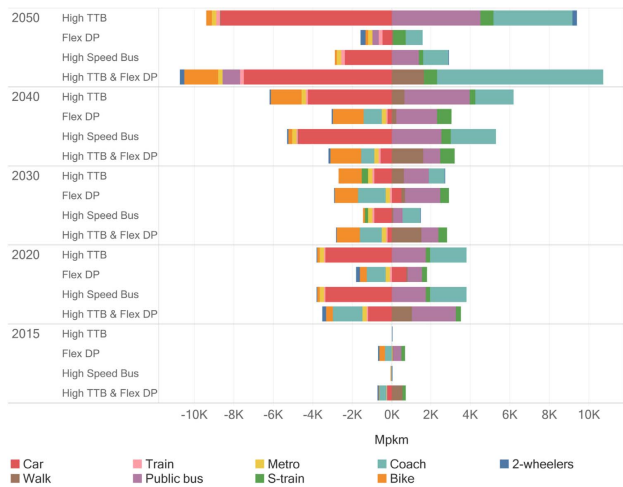


Fig. 12. Modal shift with respect to the Ref scenario of TIMES-DKMS across the sensitivity analyses.

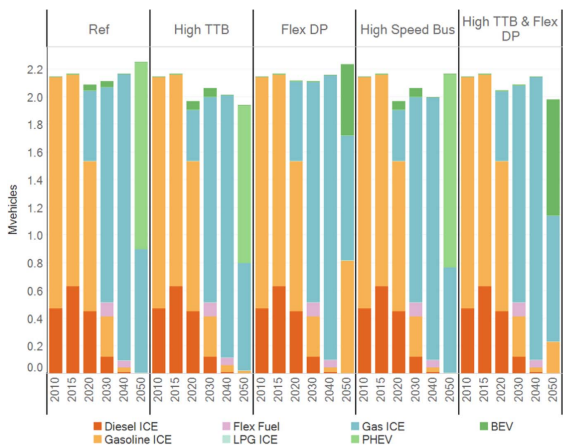


Fig. 13. Evolution of the car stock and car technologies in time, across sensitivity actions.

a significantly positive contribution to the decarbonisation of the Danish transport and energy system and thus it shall be promoted. The optimal level of modal shift identified in this study would enable Denmark to reach carbon-neutrality in 2050 with lower cumulative CO₂ emissions, lower total fuel consumption and at a lower cost for the society. According to the analyses carried out, a significant shift away from car seems difficult to realize. Policy makers would need to promote a behavioural change so that transport users accept spending more time traveling. Another option to promote shifting away from car consists in creating separate lanes for public buses, in order to increase their speed and thus their attractiveness and to slow cars down,

reducing their relative attractiveness. In all the sensitivity scenarios analysed the shift away from car is likely to benefit coach, public bus, S-train and walk. Moreover, in the long-term electricity and gas produced from fossil-free sources are expected to become the main components of the fuel mix for inland passenger transport. Bio-diesel continues being used by heavy-duty modes also in the long-term. For the car sector the analyses recognised FFV and gas vehicles as optimal transition technologies. In order to ensure the possibility to adopt such technologies, the Danish regulators shall promote the deployment of the refuelling infrastructure required and shall encourage the construction of bio-refineries and bio-digesters soon. A substantial penetration of BEVs and

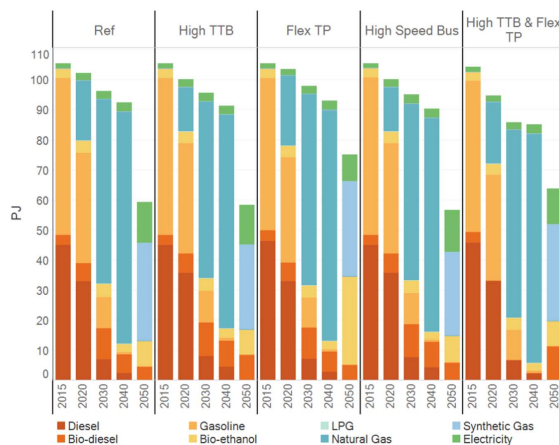


Fig. 14. Evolution of fuel consumption from passenger inland transport in time across the sensitivity actions.

plug-in hybrid vehicles (PHEVs) occurs only after 2045, due to low competitiveness with ICE based vehicles. Moreover, the analysis highlighted that in the Danish context an adjustment of the driving patterns of BEV towards longer distances is required to foster their large-scale deployment. However, a higher penetration of BEV entails a minor shift away from car and an increase of total fuel consumption.

Although the results of this study are specific for Denmark, some policy implications are transferable to other countries. The authors believe that, in any country with gross domestic product (GDP) similar to Denmark, higher TTB and higher speed of transit modes are crucial to enable a significant shift away from cars towards more sustainable means of transport. This conclusion is supported by the high sensitivity of bus travel to speed, which has also been observed in the English urban context (Pye and Daly, 2015). While giving these policy advice, we also recognise the limits of the model used for this study. The next section highlights the main limitations of the model used for this study and recommends to fellow researchers the perspective research required to overcome the current shortcomings.

5. Discussion and future research

The approach adopted for this study is based on and further elaborates on the previous works by Daly et al. (2014) and Pye and Daly (2015). The methodology draws on Daly et al. (2014) the aggregation of mode-specific mobility demands in few “cross-modal” range-specific travel demands and for the use of TTB. The inclusion of infrastructure costs, the limitation of the modal shares and the rate of shift are inspired by Pye and Daly (2015). With respect to Daly et al. (2014), the endogenous modal shift is incorporated in an integrated energy system model, thus allowing assessing modal shift dynamics with a whole-system perspective. Moreover, modes are not represented by a unique technology, but instead include many alternative technologies with different engines. With respect to Pye and Daly (2015), a first difference lies in the fact that the modeling framework is different: TIMES instead of ESME. Moreover, the focus on urban transport is enlarged to the entire national transport sector. Finally, maximal and minimal modal shares are calculated by analysing the trip distance profile in the National Travel Survey.

Although TIMES-DKMS improves the representation of transport

sector in BU optimization energy system models, the methodology presents some shortcomings. Primarily, the requirement of an extended amount of data, for which the main source is a national travel survey consistent with the geographical scope of the energy system model. The availability of such a survey is fundamental for developing the methodology adopted for this study. Fortunately, for many countries and regions travel surveys are already available. Moreover, even though the methodology does not require changing the TIMES code, the structure of the transport sector with modal shift integrated becomes more complex, as visible comparing Figs. 1 and 2. Another limitation of the study is represented by the fact that the capacity utilization levels of the infrastructures are geographically aggregated and lack of temporal detail. Increasing the time granularity of the transport demand, i.e. differentiating the transport demand in night and peak-hour time slices, would enable characterising the intra-annual and intra-day variability of the utilization levels of the infrastructure. This process entails a significant effort for recollecting the data, which is justifiable only if disaggregated transport analyses need to be carried out. However, for such type of analyses, transport simulation models (such as LTM for Denmark (Rich, 2015)) are a more effective tool. Another reflection concerns the number of distance-range classes according to which the total travel demand is split. The more the demand segments, the more precisely demand is depicted in the model and thus the more realistic is the definition of modal competition. At the same time, an increasing level of split of the demand leads to additional complexity of the model structure, which entails further modeling efforts and longer computation time. Another shortcoming of this study is the fact that the model determines optimal modal shift only based on a limited amount of parameters: levelised costs of the modes, modal speed and availability of infrastructures. On the other hand, modal choice is more complex, as consumers are affected by several attributes when they choose mode. These attributes can be aggregated in two macro classes; socio-economic and demographic attributes (e.g. age, gender, household location, income and employment), which influence consumers' preferences, and LoS variables (e.g. in-vehicle time, congestion time, waiting time, access/egress time), which define the characteristics of the modes (Rich, 2015; Cherchi et al., 2003; De Jong et al., 2004). Although modal shift in this model is only based on few attributes, to the authors' knowledge the methodology adopted for this study is state-

of-the-art within bottom-up optimization energy system models.

With the novel methodology the model finds a socio-economic optimum related to a central decision maker with full information, full foresight and perfect rationality and who takes decisions on behalf of an average transport user. However, individuals' preferences constitute a fundamental aspect of decision making in the transportation sector and distinct groups of transport users are characterized by different modal preferences. Therefore, the integration of consumers' heterogeneity as a way to differentiate their preferences is recommended as future research to improve the representation of the transport sector in bottom-up optimization E4 models. Introducing heterogeneity of transport users allows determining a solution which is the resultant of a set of decisions taken by diverse consumers, characterized by different travel habits, perceptions and thus preferences. In this way, each mode is more or less suitable for a specific consumer group and every year several modes and many different technologies contribute to fulfil the total mobility demand. Moreover, the LoS attributes characterising the modes shall go beyond speed, to include also other relevant ones, such as congestion time, waiting time and access and egress time. Finally, the modeling framework developed for this study seems promising to explore the potential contribution of increasingly recurring phenomena like car sharing, carpooling and mobility-as-a-service (MaaS) systems to reach low-carbon transport sector and energy system (Grischkat et al., 2014). In BU optimization E4 models car sharing can be represented as a new car technology characterized by a higher mileage per year, while carpooling can be represented by a new car technology with higher occupancy factor (Venturini et al., In Preparation).

6. Conclusions

The literature review in Section 2 has pointed out that so far bottom-up optimization energy system models are scarce at representing consumers' behaviour in transport and modal shift. These models determine the optimal technology mixes only minimizing the investment, O&M and fuel costs, while complying with the technological, environmental, policy and resource availability constraints. Nonetheless, beside the economic and technological dimensions, the behavioural aspect plays an important role towards achieving a sustainable transport sector. Well aware of it, this study moves a step forward in the representation of behaviour in transport within bottom-up optimization energy system models. Incorporating endogenous modal shift in such a modeling framework is a rewarding effort, as it enables assessing directly in the energy system model its contribution to a future carbon neutral energy system. Moreover, the description of the entire energy sector, from primary energy supply through conversion to consumption, allows comparing the alternative modes with a whole-system perspective. This is particularly important, considering that transport is expected to be increasingly integrated with the rest of the energy system. Section 3 describes the methodology developed for incorporating modal shift in the TIMES model of Denmark. The methodology developed enables endogenous modal shift without any change in its code. Rather, the structure of the model is adjusted in order to regulate the shift among modes based on speed and infrastructure requirement, beside cost parameters. Travel time budget ensures that slow but inexpensive modes do not prevail over the fast, yet expensive modes. The cost of the transport infrastructures evens the level of completeness of the representation of the alternative transport modes. Moreover, the representation of infrastructure limits modal shift, as saturated infrastructures require additional investment to accommodate more mobility demand. Finally, the behavioural realism of the results is ensured by the constraints reflecting the observations of a national travel survey. The TIMES model of Denmark equipped with such methodology, denominated TIMES-DKMS, allows to explore new decarbonisation pathways, co-optimizing modal shares and vehicle shares. The potential contribution of modal shift to decarbonise the Danish transport sector is analysed in Section 4. The analyses find out

that modal shift enables reaching carbon-neutral energy and transport sector in Denmark in 2050 at faster rate, with about 1.9% lower cumulative CO₂ emissions and 1.5% lower system cost with respect to the case in which modal shift is not an option. Then, four sensitivity analyses on the key variables influencing modal shift are carried out. On one side they identify to which extent different possible outcomes of the key variables enable shifting away from car and on the other side they determine the fuels and car technologies that will characterize the future Danish transport sector. The study suggests that policy makers shall promote behavioural change so that people accept longer travel time and recommends to create separate lanes for improving the acceptability of public bus. Moreover, the analyses recognise the necessity to extend the range of battery electric vehicles in order to achieve their large-scale deployment. Finally, the authors recommend that future research focuses on the integration of heterogeneity and on the incorporation of additional level-of-service attributes, in order to further improve the representation of behaviour in transport within bottom-up optimization E4 models.

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**IMPROVING THE REPRESENTATION
OF MODAL CHOICE INTO
BOTTOM-UP OPTIMIZATION
ENERGY SYSTEM MODELS – THE
MoCho-TIMES MODEL**



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Improving the representation of modal choice into bottom-up optimization energy system models – The MoCho-TIMES model

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HIGHLIGHTS

- Novel methodology for representing modal choice into energy system models is presented.
- Heterogeneity of transport users is introduced to differentiate modal perceptions.
- Preferences accounted through monetization of intangible costs.
- Value of time and level of service variables are accounted by the model.
- Approach paves the way to new policy analyses involving novel attributes.

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ABSTRACT

This study presents MoCho-TIMES, an original methodology for incorporating modal choice into energy-economy-environment-engineering (E4) system models. MoCho-TIMES addresses the scarce ability of E4 models to realistically depict behaviour in transport and allows for modal shift towards transit and non-motorized modes as a new dimension for decarbonising the transportation sector. The novel methodology determines endogenous modal shares by incorporating variables related to the level-of-service (LoS) of modes and consumers' modal perception within the E4 modeling framework. Heterogeneity of transport users is introduced to differentiate modal perception and preferences across different consumer groups, while modal preferences are quantified via monetization of intangible costs. A support transport simulation model consistent with the geographical scope of the E4 model provides the data and mathematical expressions required to develop the approach. This study develops MoCho-TIMES in the standalone transportation sector of TIMES-DK, the integrated energy system model for Denmark. The model is tested for the Business as Usual scenario and for four alternative scenarios that imply diverse assumptions for the new attributes introduced. The results show that different assumptions for the new attributes affect modal shares and CO₂ emissions. MoCho-TIMES inaugurates the possibility to perform innovative policy analyses involving new parameters to the E4 modeling framework. The results find that authority's commitment to sustainability is crucial for a paradigmatic change in the transportation sector.

1. Introduction

Transport is a key driver of economic development and it plays a fundamental role in supporting quality of life. However, it is also responsible for approximately 28% of total final energy use and for 23% of the world energy-related CO₂ emissions [1]. Transport is regarded as the most complicated sector to decarbonise, due to multiple reasons. Its

rate of growth of energy use and CO₂ emissions is 2% a year, the highest among all the end-use energy sectors. Moreover, the global growth of transportation activity has been tracking that of GDP and is strongly linked to the increase of population and incomes [2]. Mobility demand per capita in non-OECD countries is still far below the levels in OECD countries, but is expected to grow at fast pace [3]. While the power and heat sectors have many efficient and renewable energy based

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technologies available to enable a technology switch, the transportation sector lags behind. Some low-carbon technologies have appeared in the market [4], but they are still characterised by high investments costs that slow a large-scale deployment. Moreover, new transportation technologies have to face the slow turnover rate of the existing vehicle stock and the lock-in effect originated by the existing infrastructure. So far, the efforts to reduce transportation emissions by technological improvements and fuel standards have been offset by the increase of activity. The International Energy Agency (IEA) estimates in its baseline scenario a doubling of current transport energy use by 2050 and slightly more than a doubling of associated CO₂ emissions worldwide [5]. Experts agree on the strategy to pursue a reduction in transport externalities. The IEA suggests a combination of four technological and behavioural measures to promote concurrently: avoiding traveling, shifting to different modes, improving vehicle performance and switching to lower-carbon fuels [5]. Another set of measures suggested includes development of efficient technologies, changes in pricing and budgeting, changing attitudes, infrastructure supply, innovative institutional arrangements and development of new methods [6]. Given these premises, it is clear that the behavioural dimension plays a key role and that a behavioural change is a precondition for the decarbonisation of the transportation sector.

Energy system models are powerful tools for supporting long-term decision making and planning in the energy sector. In this paper we focus on a specific family of them, the TIMES/MARKAL models, belonging to the category of energy-economy-environmental-engineering (E4) optimization models. TIMES and MARKAL models have been used for more than three decades to identify least-cost resources and technology deployment pathways towards greenhouse gas (GHG) emission-free energy systems and exploring alternative scenarios under several constraints [7–12]. The major strength of E4 models lies in their ability to provide a detailed representation of the technological, economic and environmental dimensions of the integrated energy system and in their capability to explore decarbonisation pathways considering cross-sectoral dynamics and synergies. On the other hand, E4 models are still weak at depicting consumer behaviour [13–15]. This lack, to a certain extent, has reduced the credibility of E4 models' policy evaluations [16]. E4 models normally represent only a "system wide" decision maker, with perfect information and foresight and who takes rational decisions only based on pure economic criteria. However, individuals' preferences and behavioural attitudes are a fundamental aspect of decision making in the transportation sector. Therefore, the behavioural dimension shall be integrated in E4 models, to validate their application in transport policy analysis. This paper aims at filling this gap by proposing a new methodology, called MoCho-TIMES, that enables to incorporate modal choice (the choice that individuals make in selecting the means of traveling, e.g. car, public transport, bike or walk, for a specific trip) within E4 optimization models. Integrating modal choice within E4 models helps to identify the barriers limiting modal shift to zero- and low-carbon modes and to understand what kind of policies and regulation mechanisms can potentially trigger such modal shift. The theoretical basis of consumer choice is presented in Section 2, which reviews as well the representation of modal choice in transport and energy system models. Then, Section 3 presents all the aspects of this novel methodology. The results for the Business as Usual (BaU) scenario and for the alternative scenarios are analysed in Section 4, which also provides some insights on the capabilities of the approach. A discussion of the most innovative and critical aspects of MoCho-TIMES is provided in Section 5, together with recommendations for future research. Finally, Section 6 presents some concluding remarks of this study.

2. Theory and representation of modal choice

Modal choice consists of an individual facing two or more alternative transportation modes among which to choose. Given the finite

and exhaustive set of mutually exclusive choice alternatives, modal choice can be represented by discrete choice models [17]. According to the classical formulation of discrete choice models [18,19], individuals choose among the available alternatives based on an index of preference, called utility, which depends on the characteristics of the alternatives and on the characteristics of the individual. Traditionally, in discrete choice models the utility is a linear function of parameters and attributes, plus an error term, which accounts for the fact that the modeller is able to capture only a subset of all the attributes affecting modal choice [19]. These attributes are generally socioeconomic variables, which account for diversity in modal perception across the population, and level-of-service (LoS) variables, defining the characteristics of the alternatives as perceived by the consumers. Moreover, alternative-specific constants (ASC) are used to take attributes that are not under the modeller's control into account. Discrete choice models calculate the probability that a consumer chooses a certain alternative from the choice set by comparing the utilities of the different alternatives. A rational consumer will choose the alternative from which he gets the greatest utility. The most popular technique for modeling modal choice has been through logit and probit models, because they are able to account for variation of preferences across the population [17]. An important characteristic of modal choice is that it is a spatial problem: the choice of the mean of transport for a trip strongly depends on the trip length, on its origin and destination and on the local availability of public transport and transport infrastructure.

A review of the LoS, socioeconomic and demographic attributes highly relevant for mobility behaviour has been performed. Table 1 recollects the attributes affecting modal choice in some transport models found in the literature [20–26].

Transport models have a long tradition of representing modal choice. Their structure generally consists in four steps: trip generation, trip distribution, modal choice and route assignment. In the third stage, modal shares are traditionally determined through multinomial logit model (MNL) or nested logit model (NMNL) accounting for many attributes describing the observed characteristics of the modes and the observed characteristics of the consumers. These types of transport models are normally characterised by a high level of population segmentation, with the rationale that behaviour is an individual feature and therefore attempts to capture it should be pursued to provide as much heterogeneity as possible. The population is traditionally segmented based on demographics and socioeconomic variables, which allow differentiating the LoS of the modes across consumer groups. More recently, the use of attitude-based consumer disaggregation is becoming popular [27]. Considering attitudes of the population as criteria for consumer segmentation, in particular travel behaviour and willingness to change behaviour, provides a better starting point for initiatives promoting sustainable transport. In fact, it allows for establishing priorities and targeting different groups of people with ad hoc policies [26,28]. Moreover, empirical results show a link between lifestyle and sustainability in travel behaviour, claiming a paradigmatic shift in transport regulation from demand management towards lifestyle adjustments [29].

In the field of energy system modeling, the improvement of the behavioural dimension of transport and the representation of modal choice is an innovative topic. Traditionally, in optimization E4 models the end-use mobility demands are specified exogenously for each mode. Several technologies compete to fulfil the projected mode-specific mobility demands. However, technologies compete within a mode, but not between modes, thus preventing endogenous modal shift [30]. This was a limitation, because modal shift is an efficient lever to cut CO₂ emissions in the transportation sector. At first, the contribution of modal shift towards GHG-emissions reduction was determined by means of "what if" analyses, which assess the effect of exogenously assumed levels of modal shift on the whole energy system and on the environment [5,31–33]. Recently, the interest of researchers is addressing the integration of modal choice [13,16]. A review of the

Table 1
Attributes relevant for modal choice in transport models.

Attribute		LTM [20]	RMS [21]	CSTDm [22]	NTM [23]	Cherchi et al. [24]	Cherchi et al. [25]	De Jong et al. [26]
Demographic	Age	x	x	x	x		x	x
	Gender	x	x	x	x	x	x	x
	Presence of children	x	x	x	x			
	Level of education		x				x	
	Role in the family						x	
	Geography location	x	x	x	x			
	Licence ownership			x	x			x
	Car ownership	x	x	x	x	x	x	x
	Household size			x	x			x
Socioeconomic	Income	x	x	x	x		x	x
	Employment status/labour market association	x	x	x	x		x	x
	Student enrolled			x				
	Number of weekly working hours (part-time/full-time)			x			x	
	Freelance/employee			x		x	x	
LoS Car	Free time	x	x	x				
	In-vehicle time				x	x	x	x
	Monetary cost	x	x	x		x	x	x
	Congestion time	x	x	x				
	Distance	x	x	x	x			x
	Comfort					x	x	
	Ferry time/cost	x			x			
	Parking/Toll cost	x	x	x	x	x		x
LoS public transport	In-vehicle time	x	x	x	x	x	x	x
	Initial waiting time	x	x	x				
	Transfer waiting time	x	x	x	x	x	x	x
	Transfer time	x	x	x		x	x	x
	Access/Egress time		x	x	x			x
	Distance	x	x	x	x			x
	Transit fare	x	x	x	x	x	x	x
	Reliability						x	
	Comfort						x	
	Delay/Reliability					x	x	
LoS non-motorized	Travel time	x	x	x	x	x		x
	Distance	x	x	x	x	x		x

representation of behaviour in integrated energy and transport models recognised two main approaches to incorporate behaviourally realistic modal choice into bottom-up (BU) optimization E4 models [13]. The first and most traditional approach consists of linking an E4 model with an external simulation transport model that incorporates the behavioural variables in a non-linear framework (such as constant elasticities of substitution, or an MNL model) and that determines the modal shares [34–36]. The other approach consists of determining modal shares directly within the E4 model, by broadening its classical structure to integrate some transport-specific variables relevant for modal choice, such as those in Table 1 [37–39]. Despite the development of the second method requires substantial changes in the traditional model structure to incorporate transport-related attributes, integrating modal choice directly within the E4 model has several benefits. First, modal shift is evaluated with a whole-energy system perspective, which strengthens the reciprocal implications of transformations in the energy and transportation sectors. This is particularly important, as the energy and transportation sector are expected to become more strictly integrated in the future. Then, it inaugurates the possibility to assess novel policies involving transport-related and behavioural variables within an E4 model. MoCho-TIMES belongs to the second category of the taxonomy described above.

3. Methodology

The methodology proposed in this paper aims to incorporate behaviourally realistic modal choice in optimization E4 models. The E4 model used in this study is the TIMES (The Integrated MARKAL EFOM

System) model, and the approach presented is called MoCho-TIMES (Modal Choice in TIMES). TIMES is a model generator developed and maintained by the Energy Technology Systems Analysis Program (ETSAP), a Technology Collaboration Programme of the IEA [40]. It is a partial equilibrium, linear optimization model for the energy system: it determines the solution as the minimization of the sum of the total system cost of the energy system discounted to a reference year, subject to certain restrictions. TIMES is based on the bottom-up approach and thus it is said to be “technology-rich”, because it describes the technical, economic and environmental characteristics of the technologies of the energy system in detail. These characteristics make it a powerful tool for energy planners to identify the most cost-effective portfolio of resources and technologies to fulfil future energy-service demands under several constraints. TIMES is also a valuable tool for performing long-term energy system analyses, for assessing long-term dynamics across different sectors of the energy system, for testing policies affecting the energy system and for exploring alternative scenarios. A detailed description of TIMES is provided by [40] while [39,41] describe the traditional representation of the transportation sector within TIMES models. While this study integrates the methodology into a TIMES energy systems model, the intention is to produce a tool replicable by any E4 model.

The development of MoCho-TIMES relies on and requires a transport simulation model, consistent with the geographical scope of the analysis, which works as support model. This support model includes modal choice and is the main source of data for implementing the methodology hereby proposed. For this demonstrative study, the support model is the Landstrafikmodellen (LTM), also called “the Danish

National Transport Model" [42,43]. A detailed description of LTM and of its representation of modal choice is provided in Section 3.1.

This demonstrative version of MoCho-TIMES has been developed as a standalone model, which includes only the transportation sector of TIMES-DK, the integrated energy system model for Denmark [30,44,45]. The passenger transport demands are defined exogenously from the base year (BY) of 2010 until the end of the time horizon (2050) and are expressed in million-passenger kilometres (Mpkm). The modes that compete to fulfil such travel demands are: private car, bus, train, S-train, metro, bike and walk. Modes are not represented by a unique technology, but include several technologies with different powertrains. The model optimizes the system, determining the least-cost modal shares and vehicle shares that satisfy the mobility demands simultaneously, and subject to the constraints described below in this section. The novel modeling features characterising MoCho-TIMES are described in detail in Section 3.2.

The authors acknowledge previous work by [41,46,47] as source of inspiration for the approach of MoCho-TIMES. Nonetheless, a primary difference is that MoCho-TIMES enables incorporating modal choice in E4 models, while MESSAGE-Transport [41] and COCHIN-TIMES [46] improve the representation of vehicle choice.

3.1. The Danish National Transport Model LTM

The Danish National Transport Model (LTM), is a comprehensive transport demand model for Denmark [42]. Based on a simulation framework, it is able to forecast the passenger and freight transport demand in Denmark from 2010 until 2030. It is highly disaggregated geographically, in order to be able to represent mobility flows between zones: it includes 907 zones for Denmark and 371 zones for the surrounding countries. The main source of data is the Danish National Travel Survey, also denominated TU survey [48]. This survey has been investigating the travel habits of the Danish population by recollecting mobility diaries and socioeconomic data since 2006.

Within LTM, the passenger transport model consists of several interacting sub-models. First, the population-synthesizer forecasts the characteristics and the distribution of the Danish population in a given year. Then, the population is grouped into households and input into the demand model, which determines the mobility demand. Finally, such demand is iteratively assigned to the transport infrastructure (to account for the fact that an increase in demand corresponds to more congestion) until reaching convergence. The final output of LTM describes how the demand related to the modes car, bus, train, S-train, metro, walk and bike is distributed across the zones in each year. A detailed description of LTM is provided by [43]. Within the scope of this study, it is worth focusing on the travel demand model and in particular on the modal choice step, useful to understand the modeling decisions adopted for developing MoCho-TIMES. The demand model consists of three steps:

- Trip generation: it determines the total number of trips generated and attracted in each zone. For this purpose, an MNL model considering the socioeconomic characteristics of the households is used.
- Trip distribution: the number of trips generated and attracted is used to predict the most likely trip flow pattern between origins and destinations through a gravity model. The output of this step is a cross-modal origin-destination (OD) matrix, which describes the trip distribution pattern across the zones.
- Modal choice: an MNL model calculates modal shares comparing the utility functions of the modes available. The outputs of this step are the mode-specific OD matrices.

Modal choice in LTM is performed every year (y) considering a wide range of attributes. As anticipated in Section 2, the attributes relevant for modal choice are socioeconomic variables and LoS variables. The LoS covers a wide range of attributes related to travel-time components,

as shown in Equations (1)–(3) (for each year y). The travel time for car ($Time_{car,y}$) is calculated as a combination of free-flow travel time ($f_{ff_{car,y}}$), congestion time ($ct_{car,y}$), ferry-sailing time ($fs_{t_{car,y}}$) and ferry-waiting time ($fw_{t_{car,y}}$) multiplied by some penalty factors (congestion penalty (cp), ferry-sailing penalty (fs_p), ferry-waiting penalty (fw_p)). All the attributes for the LoS of car are calculated in the route assignment model. For public transport, the travel time ($Time_{pt,y}$) is determined in a schedule-based assignment model. It consists of four components, namely in-vehicle time ($inv_{pt,y}$), departure waiting time ($dwp_{pt,y}$), waiting time at the stop ($wl_{pt,y}$) and walking time ($wk_{t_{pt,y}}$), weighted by some penalty factors (waiting penalty (wl_p), walking penalty (wk_p)). For non-motorized modes the travel time ($Time_{NM,y}$) is just the travel time itself ($tl_{NM,y}$).

$$Time_{car,y} = f_{ff_{car,y}} + ct_{car,y} * cp + fs_{t_{car,y}} * fs_p + fw_{t_{car,y}} * fw_p \quad (1)$$

$$Time_{pt,y} = inv_{pt,y} + dwp_{pt,y} + wl_{pt,y} * wl_p + wk_{t_{pt,y}} * wk_p \quad (2)$$

$$Time_{NM,y} = tl_{NM,y} \quad (3)$$

In LTM, the LoS terms and the costs of each mode m are joined in a generalized time measure ($GT_{m,y}$). As shown in Eq. (4), the generalized time is obtained by taking the quotient of the cost component and the value of time (VoT).

$$GT_{m,y} = Time_{m,y} + \frac{Cost_{m,y}}{VoT} \quad (4)$$

The VoT is the marginal substitution cost between travel time and travel cost and it states how much a consumer is willing to pay to reduce the travel time of one unit [49]. The VoT adopted in LTM and in this study differs between segments, depending on the purpose of the trip and on the income level of the consumer [50]. The relationship between the VoT and the income level is shown in Table 2, from which it results that richer people are willing to spend more to save travel time.

For each mode, the generalized time and other dummy variables related to the socioeconomic characteristics of the household and to the type of zone where the trip occurs are multiplied by the model parameters (obtained through log-likelihood maximization) and finally aggregated in the utility functions [43]. The utility functions of the different modes are compared for every year within a MNL model, which determines the modal shares.

This overview of LTM is the fundamental background required to understand the main modeling choices done while developing MoCho-TIMES. In fact, MoCho-TIMES aims at being solely grounded on well-founded behaviour and consumer choice theory and relies on the data and mathematical expressions of the generalized time of LTM [48].

3.2. MoCho-TIMES: Overview and structure

Traditionally, E4 models assume a central, global decision maker who carries out decisions on behalf of the average consumer, with full information and perfect rationality while aiming to maximize the system's economic utility only accounting for costs. Under these modeling assumptions, the modal shares and the technology portfolio determined by the models represent a configuration optimum for the system, but not for the consumers' perspective. Moreover, new vehicles penetration

Table 2
Value of time by income group in DKK/hour (personal elaboration from [50]).

Income class	Personal income [100k DKK/year]	Weighted average VoT in 2010 [DKK/h]
Very low	< 200	50.8
Low	200–500	87.6
Medium	500–800	145.9
High	> 800	240.5

is characterised by a sharp pattern: as soon as a technology becomes cost-effective, it obtains the entire market share. This phenomenon is denominated “winner-takes-all” behaviour or “knife-edge” behaviour [46]. However, modal choice depends on consumer preferences and, as highlighted in Table 1, the attributes affecting it are more than purely economic. Diverse groups of consumers have different perceptions of these attributes, which results in disparate preferences towards modal adoption. Therefore, incorporating consumer heterogeneity into the modeling framework is a precondition for representing realistic modal choice behaviour. In this way, each group of transport users chooses its own optimal set of modes and technologies, thus leading to a variety of modes each year. Beside heterogeneity, representing behaviourally realistic modal choice in E4 models requires incorporating the main variables affecting it, as described in Table 1. To account for these two major requirements, the innovative methodology of MoCho-TIMES consists in two main steps:

- Divide transport users into heterogeneous groups with different modal preferences.
- Incorporate intangible costs (disutilities) that assume different values across the diverse groups of transport users.

The rest of this section provides a description of these two modeling innovations in Sections 3.2.1 and 3.2.2, then describes the other constraints required for developing MoCho-TIMES in Section 3.2.3 and finally provides an overview of the model structure in Section 3.2.4.

3.2.1. Incorporating demand-side heterogeneity

Population heterogeneity is required to account for the diversity of behaviour across different groups of consumers [51]. From a modeling perspective, incorporating heterogeneity consists of dividing transport users into groups characterised by different attitudes towards modal choice, which are reflected in different intangible costs. In MoCho-TIMES, heterogeneity is introduced by splitting the total travel demand into segments, each one associated to a specific group of transport users. Identifying the dimensions according to which transport users are split is crucial, because they need to capture the key differences between the groups and their modal preferences. The dimensions for the heterogeneity are a subset of the demographic and socioeconomic attributes in LTM:

- Region of residential location: Denmark East (DKE) and Denmark West (DKW).
- Type of residential location: urban (U), suburban (S) and rural (R).
- Income level of the household: high (H), medium (M), low (L), very low (VL).

Overall, this characterisation of heterogeneity allows to differentiate 24 groups of transport users with different preferences in modal choice, as visible in Fig. 1.

The first two levels of the segmentation introduce spatial characterisation in the model, which is fundamental when dealing with transportation analysis. The type of residential location, i.e. the type of area from which the trips depart, affects accessibility to public transport and attractiveness of car (e.g. metro and S-train are not available in DKW, waiting-time and walking-time for train are higher in rural areas and car is characterised by higher congestion-time in urban areas). Therefore, these splits enable differentiating the LoS of the modes across the population. The third split distinguishes the perception of the LoS of the modes for consumers living in the same residential location by considering their income levels. The rationale behind such a split is provided by Table 2, which shows that the income level affects the VoT, so that people weigh time and cost in a different way depending on

their wedge. Consumer segmentation according to the income level is based on TU survey [52], while the split according to the type of residential location is based on the OD matrix of LTM. As shown in Fig. 2, the zones of LTM are labelled as urban, suburban and rural, taking the density and the total population in every zone into account [53]. Matching the travel demand distribution provided by the OD matrix with the U/S/R label reveals how the total travel demand distributes across the types of urbanization.

3.2.2. Quantifying modal preferences

After heterogeneity is integrated by splitting the mobility demand into segments corresponding to groups of transport users living in the same type of residential location and with similar income level, the intangible costs need to be incorporated in the model. These serve to capture the non-economic factors affecting modal choice into the expression of the generalized cost, as well as to differentiate modal perception across the heterogeneous demand segments through monetization. In order to incorporate intangible costs in the model, the expression of the modal cost is changed. The generalized cost (GC) characterising each mode (m), per each consumer group (cg) and in each year (y) is the sum of three terms, as shown in Eq. (5): fuel cost (FC), non-fuel cost (NFC) (including operation and maintenance cost and investment cost) and intangible costs ($InCos$).

$$GC_{m,sg,y} = FC_{m,y} + NFC_{m,y} + InCos_{m,sg,y} \quad (5)$$

The latter term of Eq. (5) is the one that introduces the non-monetary costs perceived by consumers and that differentiates the perception of the mode across consumer groups. In fact, the same mode has associated different intangible costs ($InCos$) for each consumer group. This is due to the expression of the intangible costs, shown in Eq. (6): it is the product of the LoS, which is affected by the type of residential location, and the VoT, which is related to the income level of the cg . Other attributes that also contribute to the utility of a transport mode, e.g. car ownership, presence of children in the family, are not included in this formulation.

$$InCos_{m,sg,y} = LoS_{m,sg,y} * VoT_{m,sg,y} \quad (6)$$

The expressions of the LoS in MoCho-TIMES are the same as those in LTM described in Eqs. (1)–(3), in order to maintain consistency with the support model. In particular, the LoS in MoCho-TIMES are obtained aggregating the quantities of LTM at the level defined by the heterogeneity. Another important difference between MoCho-TIMES and the support model is that the latter characterizes modal perception through the generalized time (see Eq. (4)), while the novel model adopts the generalized cost. As optimization models take decisions based on least-cost criteria, the monetization of the LoS is required. It is worth noting that all the technologies belonging to the same mode are characterised by the same intangible cost. Nonetheless, the methodology is flexible enough to allow differentiating this cost across technologies, if required.

Fig. 3 compares the intangible cost perceived by VL income consumers living in the three types of residential locations for Denmark East in 2030 with the non-fuel cost (the sum of the capitalized investment costs and operation and maintenance costs) and fuel cost. In all the residential locations and for all the modes, intangible costs account for the greatest share of the generalized costs. Moreover, Fig. 3 shows that the intangible costs assume diverse values for the three types of residential location, which proves that the differences in modal perception of consumers living in urban, suburban and rural areas are reflected in the intangible costs.

Consumers with different income levels are characterised by distinct magnitudes of intangible costs, as visible in Fig. 4 (for suburban areas in Denmark East in 2030. Figures for the other urbanization types, in Denmark West and in other years are slightly different). This is

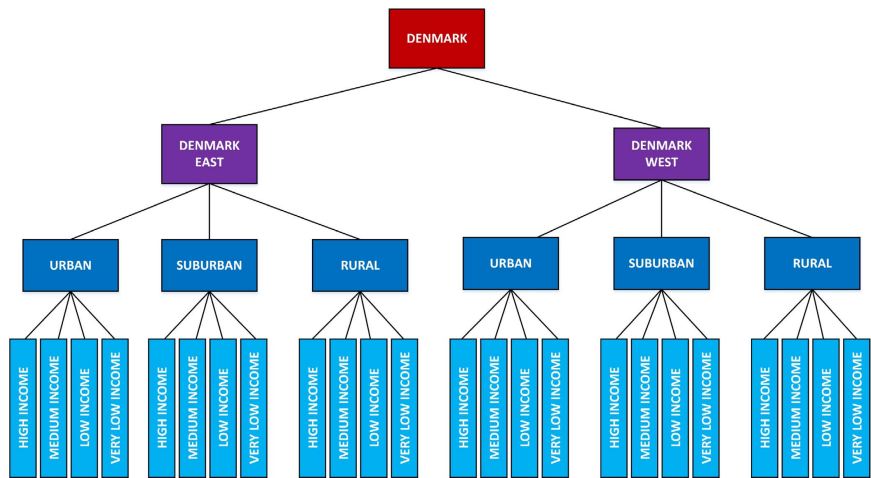


Fig. 1. Schematic illustration of heterogeneous consumer groups.

evidence of the fact that the VoT is proportional to the income level (see Table 2). As a consequence, MoCho-TIMES adopts the modes characterised by better LoS to move high income groups, while for less attractive modes such as walk and bike it prioritizes consumers with lower income level. This is done while respecting the constraints described in Section 3.2.3.

3.2.3. Incorporating the other variables influencing modal choice in MoCho-TIMES

In addition to consumers' heterogeneity and intangible costs, MoCho-TIMES also incorporates other parameters that influence modal choice. These are the monetary budget, availability of transport infrastructures, travel time budget, travel patterns, maximal modal shares and maximum rate of shift. A description of these features is provided in this section.

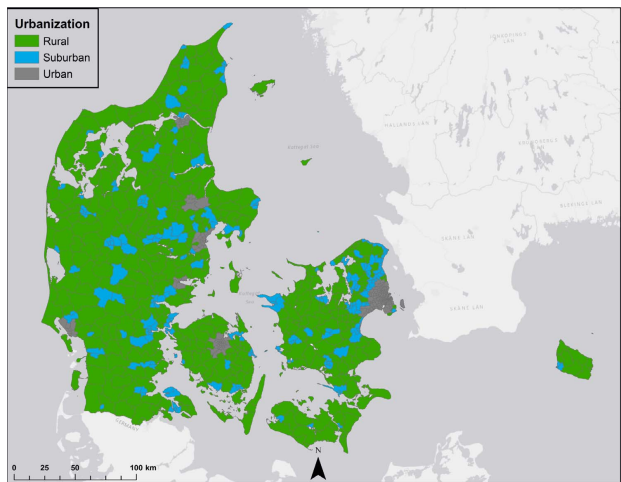


Fig. 2. Classification of the zones of LTM by type of residential location.

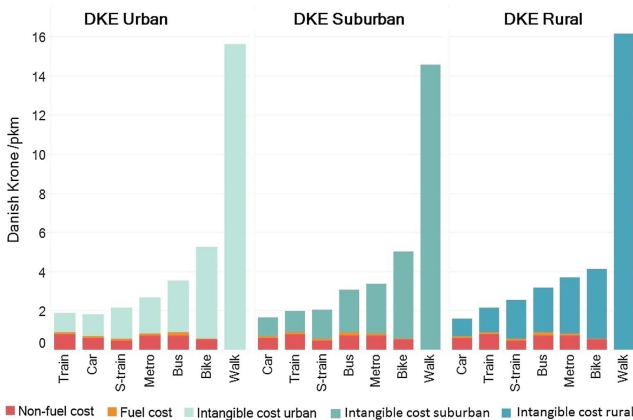


Fig. 3. Comparison of non-fuel cost, fuel cost and intangible cost for VL income consumers in Denmark East in 2030 in the three types of residential locations.

3.2.3.1. Monetary budget. Traditionally, E4 models determine the optimal configuration of the future energy system by comparing the lifetime costs of the technologies available and the fuel production chains as perceived by a central energy planner. The costs accounted are related to the supply of the energy resources and to the technology capacity expansion and operation: investment costs, fixed and variable operation and maintenance costs, fuel costs and delivery costs. Nonetheless, when incorporating modal choice in the modeling framework, the perspective of the central energy planner must be substituted with that of the consumers. These consumers also perceive

other costs, such as availability of infrastructure, ticket fares for public transport and fuel taxes, parking cost, vehicle registration tax (VRT) and ownership tax for private car. In order to render comprehensively the mechanism of consumers' modal choice, these costs have been integrated into MoCho-TIMES. Fares for public transportation modes are calculated from the TU Survey [52], while for car the cost of parking is obtained from [54], the insurance cost from [55] and the registration and ownership taxes from [56]. Nonetheless, the central planner does not face these costs, which hence shall not be accounted in the total system cost. Therefore, these consumer-perceived costs of

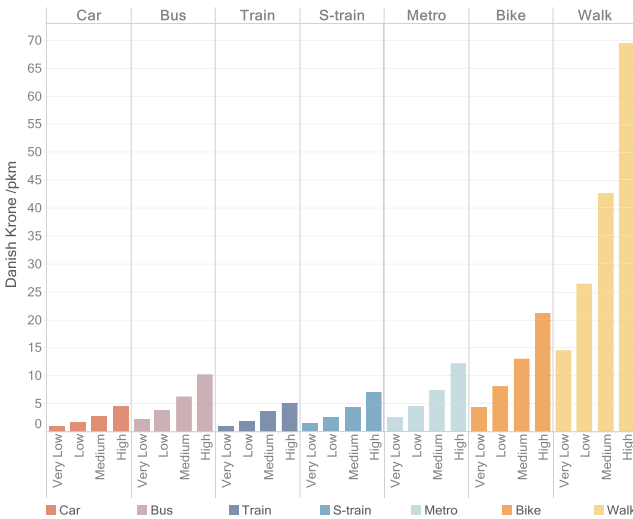


Fig. 4. Intangible costs faced by consumers living in suburban areas in Denmark East in 2030 per mode and per income level.

driving car and using public transport are included in the model as commodities, which are consumed by the modes in order to fulfil the travel demands. The model tracks how much consumer-perceived cost commodities are consumed by the four income groups (H, M, L and VL). In addition, income group specific monetary budgets limit the consumption of the consumer-perceived cost commodities. The monetary budgets are obtained considering the monetary requirement in the BY of MoCho-TIMES calibrated to the baseline demand projection of the LTM. The monetary budget ensures that the different classes of income groups do not spend for mobility more money than historically observed. At the same time, since the monetary budget includes both transit and private car, the constraint does not fix the relative modal shares of these two classes of mode and allows modal shift.

3.2.3.2. Transport infrastructure. Transport infrastructure is a key driver of travel demand and modal choice [6,57,58]. In transport simulation models such as [20,21], the level of utilization of the road network affects congestion time and travel time for car and thus influences the LOS. On the other hand, in energy system models transport infrastructures are more rarely represented. The rationale for incorporating infrastructure in MoCho-TIMES is that there must always be enough infrastructure capacity to accommodate the travel demand. There are five transport infrastructures represented in MoCho-TIMES: road for bus and car, three railways for train, S-train and metro and bicycle lane for bike. These transport infrastructures are not represented explicitly in the model, but as commodities that the modes consume in order to fulfil the mobility demand. The existing infrastructure commodities are free, but limited. The amount of extra travel demand with respect to the BY that the existing infrastructures can accommodate before saturating depends on their capacity utilization levels. These are calculated for each infrastructure as the ratio between the maximum traffic volume and the infrastructure capacity [59,60]. After the existing infrastructures saturate, the model accommodates the extra travel demand by investing in new infrastructures, with a cost associated [61,62]. More details regarding the representation of transport infrastructure are provided in [39].

3.2.3.3. Travel time budget. The rationale of the travel time budget (TTB) has been provided by [63], which claims that, in different geographical areas, historical periods and socioeconomic contexts, people dedicate the same amount of time to mobility. The TTB has been incorporated in MoCho-TIMES to ensure that transport users dedicate to mobility an amount of time consistent with historical observations. From the modeling perspective, the TTB is a constraint that limits the availability of the travel time commodity, which is consumed by all the modes and technologies when fulfilling the travel demands. Travel time is constant across all the technologies belonging to the same mode (with the exception of electric and normal bikes). Moreover, travel times are specific to the region and type of residential area from which the trip originates. Travel times are obtained from TU Survey [52] as described in [39]. The TTB per capita for the BY of MoCho-TIMES is 58.4 mins/day, very similar to that observed by TU survey, which is 54.8 mins/day [52]. The difference between the two quantities is due to the fact that TU survey includes more modes in the analysis.

3.2.3.4. Modal travel patterns, maximal modal shares and maximum rate of shift. MoCho-TIMES characterizes the modal travel patterns, which define how modes contribute to meet the travel demands. The modal travel patterns for the BY, shown in Table 3, are obtained from TU Survey [52]. Some additional flexibility is provided to the model to fulfil the future travel demands. From year 2012 onwards, the travel patterns of private modes (car, bike and walk) are relaxed by 12% with

Table 3
Modal travel patterns in 2010.

	Denmark east			Denmark west		
	Urban	Suburban	Rural	Urban	Suburban	Rural
Car	33%	35%	31%	18%	34%	48%
Bus	56%	25%	19%	32%	31%	37%
Train	52%	30%	18%	39%	37%	24%
Metro	92%	3%	5%			
S-train	75%	20%	5%			
Bike	50%	28%	22%	34%	24%	43%
Walk	72%	21%	7%	39%	40%	21%

respect to the BY, while those of public transport (bus, train, S-train and metro) are relaxed by 10%.

Modal competition in MoCho-TIMES is regulated also through a set of constraints that limits the maximal modal shares in 2050. These upper bounds are calculated comparing the modal travel patterns in Table 3 with the distribution of the total travel demand across regions and urbanization types. The rate of modal shift is also limited, based on linear interpolation between the modal shares in the BY and the maximal modal shares in 2050. A more extensive discussion of these approaches is given in [39].

3.2.4. Structure of MoCho-TIMES

A simplified schematic overview of the structure of MoCho-TIMES is provided in Fig. 5. Each mode can fulfil 24 demand segments, which correspond to the 24 heterogeneous consumer groups differentiated by region, type of residential location and income level (see Fig. 1). The modes have an intangible cost associated to each demand segment. These costs monetize the modal perception of the consumer group associated to the demand segment and are calculated outside of the model as shown in Eq. (6). Moreover, each mode contributes in its specific way to fulfil the demands, as defined by the travel patterns (see Table 3). To fulfil the travel demands, the modes do not just consume fuels, as in traditional TIMES models, but require in input also other commodities: infrastructure, travel time and consumer-perceived costs. These commodities are provided by some processes (on the left part of Fig. 5), which availability is bounded. The existing infrastructures (represented by just one process in Fig. 5) are limited, and when saturated the model can endogenously decide to invest in new infrastructures, which have associated costs. The TTB limits the overall consumption of travel time. The monetary budgets for the four income groups (represented by just one process in Fig. 5) limit their expenditure in public transport and private cars.

3.3. Scenario definition

Five scenarios are analysed in this study: a BaU scenario and four alternative scenarios that involve different LoS of modes, consumer perceptions, taxation schemes, infrastructure deployments and incentives to public transport with respect to the BaU scenario. The two dimensions for the alternative scenario matrix are authority commitment (A) and individual commitment (I), both characterised by the dichotomy high/low (HI/LO). A schematic overview of the four alternative scenarios is provided in Fig. 6.

A general description of the four alternative scenarios follows. More details on the assumptions for the BaU and alternative scenarios are provided in Table 1 of Appendix A:

- **HIA-HII (High Authority commitment – High Individual commitment):** leaders and consumers are aligned in fighting climate change and

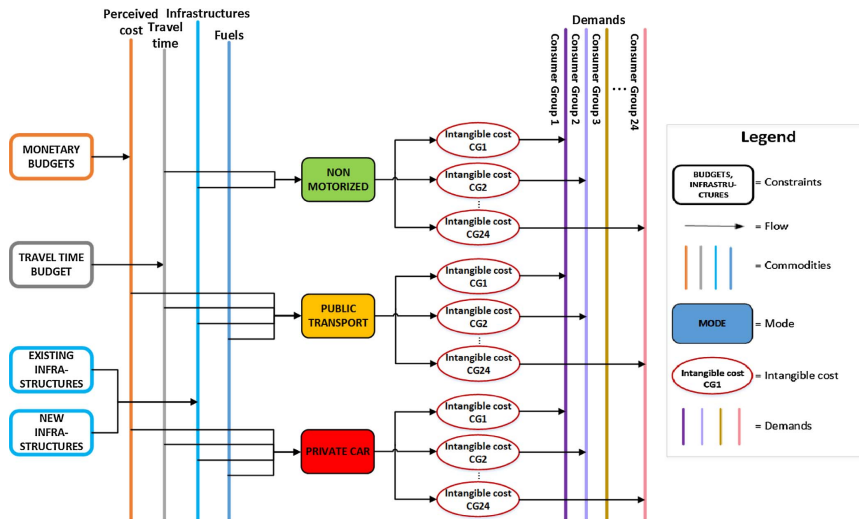


Fig. 5. Scheme of the structure of MoCho-TIMES.

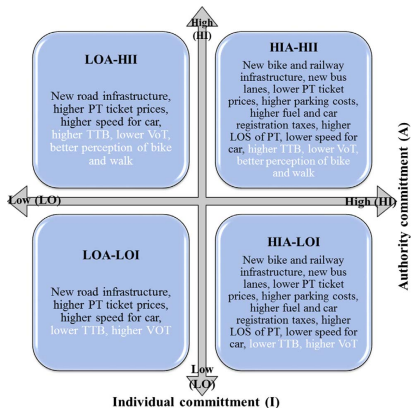


Fig. 6. Scenario matrix, with authority commitment and individual commitment as dimensions.

local air pollution, aiming at a more sustainable transportation system. After 2020, the authority builds new bike lanes, bus lanes, one new metro line, one new S-train line and a new electrified railway. The Government also encourages the use of public transport by decreasing the fares and increasing parking prices, especially in urban areas. In order to promote the adoption of alternative fuelled vehicles (AFV) and efficient vehicles, the authority also increases the taxes on diesel and gasoline from 2020 and on natural

gas from 2030. The VRT for cars in 2020 is set at the same levels as before the reform of 2016 [64] for fossil fuelled cars. On the other hand, plug-in hybrid (PHEV) only pay 20% of payable VRT and battery electric vehicles (BEV) and fuel cell electric vehicles (FCEV) are exempted from VRT. Following the investments in infrastructure, the careful urban planning and the integration of the public modes, the LoS of public transport after 2020 is assumed to improve by approximately 10% in this scenario. Instead, the lack of investments in new roads and the increase of public lanes lead to a decrease in car speed. High individuals' commitment towards sustainability consists of a greater willingness to spend time traveling (+10% TTB with respect to BaU), a better perception of the walking time and waiting time associated with the use of transit, a better perception of bike and walking, a lower availability to spend time in traffic with car and a reduction of the value of time (−10% VoT with respect to BaU).

- **HIA-LOI (High Authority commitment – Low Individual commitment):** the Government strives to promote a sustainable transportation sector and puts in practice the same measures as described in the previous scenario (HIA-HII). Nonetheless, regarding the individual commitment, transport users are reluctant to change behaviour. After 2020, consumers are more willing to spend time in traffic when using car transport with respect to BaU, but less willing to spend time accessing the public transport station and waiting for transit, and do not perceive any attractiveness in walking and cycling. They dedicate less time to mobility (−5% TTB with respect to BaU) and give a high value to savings of travel time (+10% VoT with respect to BaU).
- **LOA-LOI (Low Authority commitment – Low Individual commitment):** this scenario corresponds to a future characterised by general disinterest towards climate change and environmental issues. The authority only builds new road infrastructure, thus improving only the LoS of car and bus. Moreover, it does not incentivize public transport fares, does not set new taxes on fuels, nor increase the VRT of

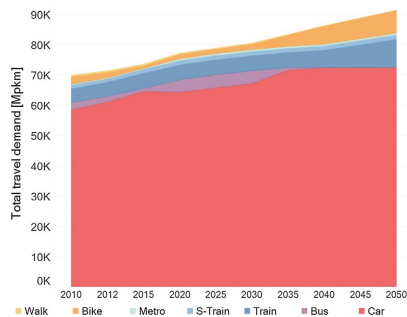


Fig. 7. Aggregated modal shares in the BaU scenario.

fossil-fuelled cars. Consumers' low commitment towards sustainability is described in the same way as for the individual's commitment of HIA-LOI.

- **LOA-HII (Low Authority commitment – High Individual commitment):** individuals alone commit towards a more sustainable transportation sector, without any support from the Government. This scenario is characterised by the same variables as LOA-LOI concerning the authority commitment and by the same variables as HIA-HII concerning the individual commitment.

4. Results

MoCho-TIMES endogenously determines the modal shares from 2010 until 2050. It also determines the optimal technology fleet within each mode, the fuel consumption, fuel prices, investments in new transport infrastructures, emissions and other traditional outputs from E4 models. This section is structured as follows: firstly, Section 4.1 describes the results for the BaU of MoCho-TIMES, compares them with those of the support model LTM and focuses on the capability of the model to observe how modal shift occurs across diverse consumer groups. Secondly, Section 4.2 tests the behaviour of the model via a scenario analysis that evaluates how alternative assumptions for the newly incorporated variables affect modal share and CO₂ emissions.

4.1. Business as Usual scenario

Although MoCho-TIMES allows to analyse many aspects of the transportation sector, the focus of this study is primarily on modal shares, which are determined endogenously within the model. Fig. 7 shows the modal shares for the BaU scenario, aggregated on all the demand segments. During the time horizon of the model, the total travel demand increases by about 31%. In the long-term, car transport is responsible for the majority of this increase, with a significant contribution from trains and bikes. In the medium-term, the activity of cars is reduced due to the uptake of buses. These dynamics occur due to the unchanging vehicle prices of new cars in the medium-term, coupled with an improvement in the LoS of buses, which reduce the intangible costs for consumers. Nonetheless, after 2035 buses stop being used because the cost of car technologies significantly reduce, resulting in a shift towards cars. As road infrastructure saturates the model chooses to seize investing in more, but rather to adopt more train and bike transport. The increase in the use of metro and S-train is largely limited

by the fact that it only exists in DKE and that it would require expensive investments in additional infrastructure. Walking strongly reduces with respect to the BY due to its high intangible cost.

A comparison between the modal shares of MoCho-TIMES with those of its support model LTM is shown in Fig. 8 for the years 2010, 2020 and 2030. The time horizon of LTM is limited to 2030, and so the comparison is drawn until this year. This comparison shows that MoCho-TIMES is able to reproduce the results of its support model satisfactorily. The modal shares of the two models in 2010 are identical and in 2020 and 2030 the main differences consists in the fact that the market share of bus transport for MoCho-TIMES is higher with respect to LTM, at the expense of train transport.

MoCho-TIMES has the capability to analyse how modal shift occurs in the different types of residential locations (urban, suburban and rural) while providing insights on modal adoption for each consumer group. The modal shares of Fig. 7 are the aggregated result of the underlying choices of the heterogeneous consumers, which are characterised by diverse modal perceptions and preferences. The differentiation of the intangible costs across consumer groups allows for modal shares to vary by type of urbanization and income level, as shown in Fig. 9. The aggregated patterns of modal adoption shown in Fig. 7 (e.g. mid-term buses uptake, car saturation and long-term uptake of bikes and trains) are also visible at a disaggregated level in Fig. 9. The opportunity of observing modal shares at a consumer group level is extremely important, as it provides insight to which segmentation(s) modal shift actually occurs and allows to differentiate the willingness to adopt sustainable modes across different transport users. In this way, it is possible to identify groups which are most averse to modal shift, to understand their reasons and to tackle them with ad-hoc policies. Furthermore, Fig. 9 shows that transport users who live in rural areas have fewer options available to shift away from travel via car, which leads to an increase of the use of car across all income groups in rural areas. Urban and suburban areas are served by a wider variety of modes, which allows lower income classes to decrease their use of car transport after 2040 with respect to the BY. The use of cars in urban areas begins to plateau in the medium to long-term. Across all types of urbanization, VL and L income classes are witnessed to be more willing to shift away from car as a mode of transport, while wealthier consumer groups are more reluctant to reduce their dependence on car. In particular, high-income groups have a tendency to use fast modes of transport to travel, while their adoption of slow modes, e.g. bike, is the lowest. In urban areas, there is a shift away from car transport mainly towards train and bike transport. The increase in train transport in this case is due to the better LoS offered by train in the long-term, such that its intangible costs become lower than that of car counterpart. The increase in the use of train, which is the fastest mode, leads time savings large enough to enable an increased use of bike, which is slow yet not expensive, while respecting the TTB constraint.

4.2. Alternative scenarios

The sensitivity of MoCho-TIMES to the assumptions of key variables is hereby tested via illustrative scenarios, which explore how alternative assumptions can result in larger share of public transport and low-carbon modes that can potentially reduce CO₂ emissions. The costs of these scenarios, such as total system cost, investment cost, O&M cost and fuel cost related to the modes, cost of new infrastructures and subsidies are excluded from the discussion.

For the four scenarios described in Section 3.3, MoCho-TIMES determines the modal shares shown in Fig. 10. As expected, the diversity of assumptions for the variables results in different modal shares. The two scenarios that imply high commitment by the authority (HIA) are characterised by the lowest increase in the use of car transport. The

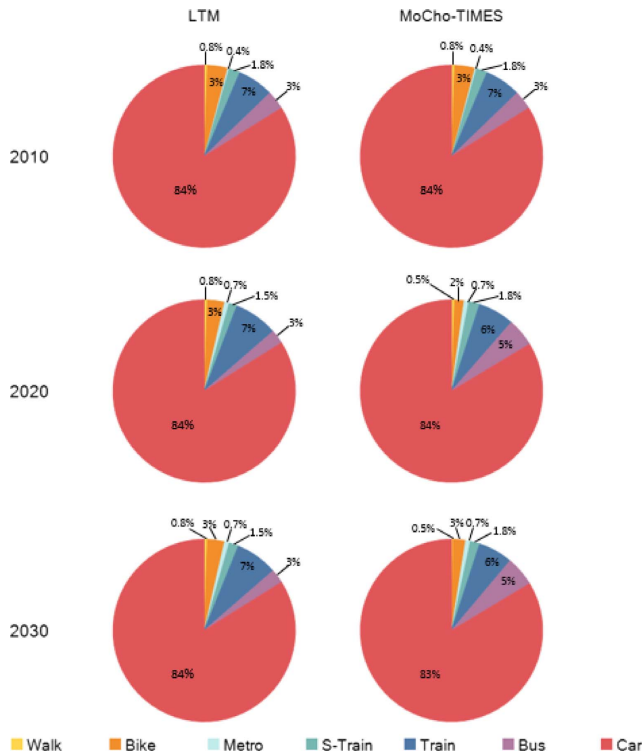


Fig. 8. Comparison of modal shares between LTM and MoCho-TIMES for 2010, 2020 and 2030.

HIA-HII and HIA-LOI scenarios mostly differ in the fact that in case of high commitment of transport users (HII) bike transport plays a major role in fulfilling future travel demand, while in case of low consumer engagement train transport is the mode characterised by the highest increase in the long-term. In the scenarios characterised by low commitment from the authority (LOA-HII, LOA-LOI), car is the main mode meeting the future extra mobility demand. These two scenarios mostly differ in that bike transport is used more frequently in the case of high commitment of consumers (but still less than in HIA-HII and BaU), while in case of low commitment of individuals, buses and trains are preferred alternatives. In particular, buses feature the most in the medium-term and trains in the long-term. Moreover, in these scenarios metro and S-train do not gain as much importance as in case of high authority commitment. While it is not reported in this paper, MoCho-TIMES has the ability to analyse how different consumer groups shift mode as a consequence of different assumptions, as shown for the BaU scenario in Fig. 9.

The trend of CO₂ emissions from the Danish transportation sector is compared for the BaU scenario and for the four scenarios analysed in

Fig. 11. The HIA-HII and HIA-LOI scenarios, which are characterised by lower increase of car usage and high use of public transport and bike transport, in the long-term reach a deep cut of CO₂ emissions. On the other hand, the scenarios corresponding to a low commitment of authority imply even higher CO₂ emissions than in the BaU scenario. Even if these results are relative to the Danish context, they highlight that the authority commitment towards sustainability is of primary importance to significantly reduce the carbon intensity of the transportation sector. If the Government does not commit towards sustainability, all the efforts of individuals alone are mostly nullified.

5. Discussion and future research

MoCho-TIMES moves a step forward in the representation of human behaviour in BU optimization energy system models and improves the representation of consumers' choice in transport. The methodology proposed does not require any change in the TIMES code, although the model structure must be restructured, as shown in Fig. 5. Moreover, a significant amount of data is required and the incorporation of the

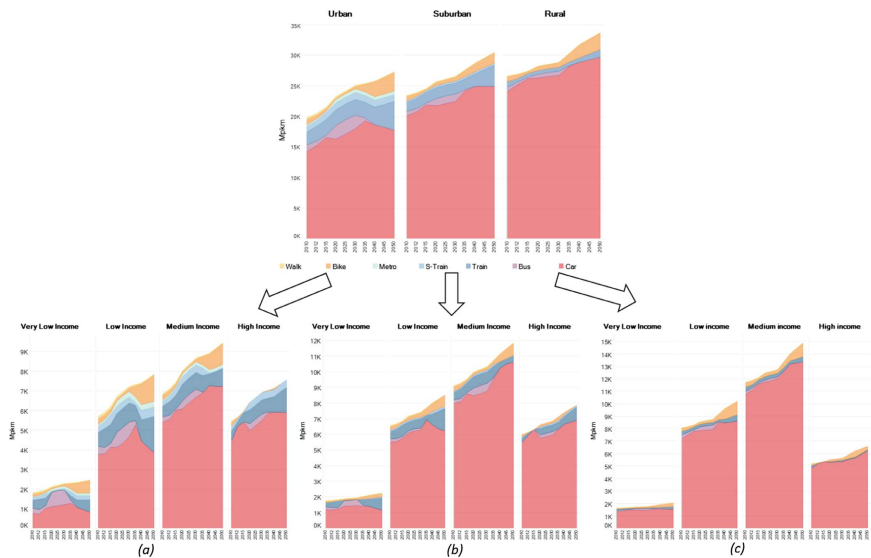


Fig. 9. Modal shares for the three types of residence location, disaggregated at income group level (aggregated for DKE and DKW). (a) urban, (b) suburban, (c) rural.

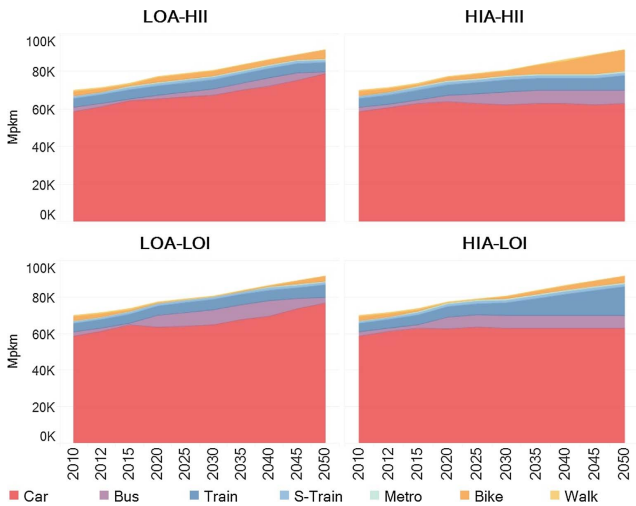


Fig. 10. Modal shares in the four scenarios. HIA-HII: High authority commitment - High Individual commitment; HIA-LOI: High authority commitment - Low individual commitment; LOA-LOI: Low authority commitment - Low individual commitment; LOA-HII: Low authority commitment, high individual commitment.

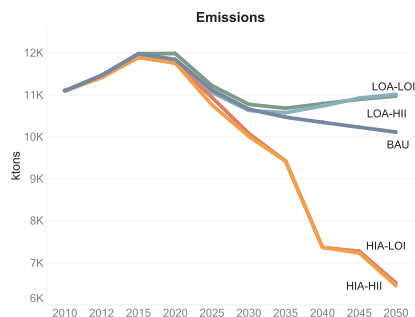


Fig. 11. Trend of CO₂ emissions from BY until 2050 in BaU scenario and in the four scenarios analysed.

intangible costs implies several extra model calculations.

The main limitation of MoCho-TIMES is that its development requires a transport simulation model with the same geographical scope as the E4 model. The transport model works as a support model, providing a disaggregated description of the mobility demand (via an OD matrix) and of the LoS attributes. Fortunately, for many countries and regions dedicated transport models are available, e.g. LTM for Denmark [20], RMS for Ireland [21] and CSTDM for California [22]. Even when a transport simulation model for the geographical area analysed is not available, many of the data required for incorporating modal choice in E4 optimization models can be obtained from a geographically consistent travel survey. Concerning the use of transport models as support to the development of MoCho-TIMES, it is worth noting that the time horizon of the energy system model and of the transport simulation model may differ. In fact, E4 models are mainly used for exploring energy scenarios in the long-term, while transport simulation models are used to forecast the transport demand and the traffic distribution in the medium-term. Therefore, the latter category relies on data related to the socioeconomic characteristics of the population and to the availability of infrastructure. This is the case for LTM, which forecasts the development of the Danish transportation sector until 2030, while MoCho-TIMES models the transportation sector with a time horizon of 2050. The difference in time horizon between the two models implies that the modeller has to make several assumptions for the transport-related variables between 2030 and 2050. A possible way to overcome this limit is performing some scenario and sensitivity analyses on the uncertain variables, as done in Section 4.2.

A further possible source of challenges lies in the fact that modal choice within MoCho-TIMES is determined at a highly aggregated level, for macro clusters of consumers. As behaviour is an individual trait, any attempt to capture it should be pursued at individual level. The scientific literature shows that modal choice is deeply affected by behavioural features, hence transport models simulate modal choice at individual or household level [17]. Compared to these levels of detail, the heterogeneity integrated in MoCho-TIMES falls short. However, it manages to capture some variability of modal preferences across the population, enough to overcome the “mean-decision maker” perspective [41]. In fact, by splitting the mobility demand in several segments corresponding to different consumer groups, the model determines the optimal modal shares separately for each consumer group. The mix of modes within the demand segments is obtained from the combined action of the travel pattern constraints and the maximal modal shares, which respectively set

some shares on how modes fulfil the demands and regulate the maximum penetration of each mode. The variation in modal shares across demand segments (see Fig. 9) is obtained from the intangible costs, which differentiate consumer-specific modal preferences, and from the difference in the monetary budget across income groups.

The authors find that the level of heterogeneity incorporated in this study is adequate for the scope of the analyses that are normally carried with E4 models. Nonetheless, the approach allows to define the number of heterogeneous consumers group in a flexible way. If an analysis needs a more refined level of heterogeneity for exploring consumers' choices more in depth, it is possible to split the overall mobility demand according to more dimensions. Possible additional dimensions are the socioeconomic and demographic attributes listed in Table 1. Another valuable criterion for demand splitting is according to trip distance, which would enable a better regulation of competition between modes, as done in [39]. Theoretically, having as many demand segments as the number of households, or even individuals, would be ideal. Nonetheless, a high number of demand segments leads to model intractability. Therefore, finding a good trade-off between model size and representation of the population is crucial. An important effort for the modeller is that of determining the minimum number of dimensions that allows to create an exhaustive distinction between the main consumer groups. The comparison of the results of LTM and MoCho-TIMES until 2030 proves that the latter is able to reproduce the results of its support model suitably, even if with aggregated transport demands. An alternative approach to represent population heterogeneity and the differences of modal perception across the consumer groups consists in implementing the “clones”, deviations from the “mean-consumer” perspective equivalent to the error term of the utility function of discrete choice models [46,47]. For this approach, it is important to choose the right amount of clones that ensures variability of results, while avoiding model intractability, as observed by [13]. The use of the clones would ensure enough variation in the results as to avoid the “winner-takes-all” phenomenon.

Another shortcoming of MoCho-TIMES lies in its vague spatial framework. Transport models require a precise description of the spatial context, as they simulate modal choice after the origin and destination of the trips are identified (see Section 3.1). On the other hand, in MoCho-TIMES the only spatial reference is the region and the type of residential location (urban, suburban and rural). Therefore, the LoS attributes define the performances of the modes only at level of macro area. However, MoCho-TIMES is not meant to study what mode is adopted for a certain trip, but rather to analyse modal choice dynamics at aggregated level and to explore how modal shift and long-term changes in the whole energy system affect each other.

The final reflection concerns the ability of MoCho-TIMES of depicting modal choice in a behaviourally realistic way. Consumers are characterised by perfect-information, perfect-foresight and perfect-rationality, due to the intrinsic nature of TIMES models. Even in transport simulation models, utility maximization, perfect-rationality and perfect-information are the assumptions underlying modal choice modeling. However, these situations are far from the reality, because choices are biased from optimality in many aspects. Recent studies on travel behaviour claim that choice mechanisms for modal choice are more complex than described by MNL models [58,65]. Consumers deviate from rationality and utility maximization in three respects: non-standard preferences, nonstandard beliefs, and nonstandard decision making [66]. These studies advocate a more extended use of evidences from behavioural economics in transport models in order to improve the representation of modal choice and other aspects of travel behaviour.

This paper has presented and tested the novel approach of MoCho-TIMES as a standalone mode, including only the transportation sector of

TIMES-DK. The authors recommend as next step of research the integration of MoCho-TIMES within a whole energy system model, in order to introduce behaviourally realistic modal shift as an option to decarbonise the energy system. This enables assessing the effect of energy system dynamics on modal shares and vice versa, within a unique modeling framework. On one side, it allows to analyse how variations in the LoS of the modes and consumers' perception of the modes affect the rest of the energy system and, on the other side, how modal shares and fuel consumption in the transportation sector are influenced by decisions in the power and heat and other end-use sectors. It is especially important to integrate transport and energy system analysis in a unique framework, given that the transportation sector is expected to become increasingly integrated into the energy system, with more interconnection and cross-sectoral influences. Once MoCho-TIMES is integrated within the whole energy system, several new policy analyses can be performed with respect to traditional E4 models. To this extent it is worth noting that the intangible costs act for the transportation sector as an additional barrier to its decarbonisation. As observed by [41], when incorporating heterogeneity and intangible costs into the model, a higher carbon tax is required to achieve an equivalent GHG abatement with respect to a traditional E4 model. Although the methodology allows having a better insight on consumer choice, the inclusion of an extra cost-term makes CO₂ reduction measures for the transportation sector more expansive and thus more unlikely to happen than in other sectors. Consistency across sectors is fundamental to avoid this issue and therefore the improvement of the representation of behaviour in the transportation sector shall be matched with the inclusion of hurdle rates and intangible cost in the other energy sectors. Besides, it is important to consider that for MoCho-TIMES the total system cost is obtained subtracting the intangible costs out of the objective function. This is done to only account for the monetary costs incurred by the central planner.

6. Conclusions

MoCho-TIMES proposes a novel methodology to incorporate modal choice within BU optimization energy system models. For this class of models, it fills the gap regarding the representation of behaviour in the transportation sector and inaugurates the possibility to perform scenario and policy analysis involving transport-related and soft variables, as advocated by [13]. For this study, the methodology has been developed and tested in the standalone transportation sector of Denmark. The approach is grounded on the consumer choice modeling theory, described in Section 2. The methodology of MoCho-TIMES is described in detail in Section 3. A transport simulation model consistent with the geographical scope of the E4 model in which modal choice is meant to be incorporated is required. The transport model works as a support model, which provides the data and the mathematical expressions for integrating modal choice in the E4 framework. MoCho-TIMES introduces heterogeneity of transport users and intangible costs to differentiate the LoS and the modal perception across different consumer groups. Overall, the innovative model structure and the constraints described in Section 3.2.4 contribute to the heterogeneity in outcomes: every year several modes contribute to fulfil the total travel

demand, each mode being more or less suitable for a specific consumer group. Modal shares are not determined exclusively according to least-cost criteria, because MoCho-TIMES captures also other attributes affecting modal choice: the LoS of the modes and the socioeconomic and demographic characteristics of the consumer groups. This is the first study to the authors' knowledge that equips E4 models with modal choice without the use of an external model. This new feature on the one hand incorporates real household's modal preferences and perceptions, which increases the credibility of the policy analyses carried-out. On the other hand, it enables to understand in the same modeling framework how changes in modal perception, improvements in the LoS of the modes, technology improvements, infrastructure availability, market conditions and policy levers can lead to deploy low-carbon technologies that contribute to achieve a carbon-neutral transportation sector. These new capabilities of MoCho-TIMES are demonstrated in Section 4, which analyses in four illustrative scenarios how alternative assumptions of key variables influence modal shares and CO₂ emissions. Another praise of MoCho-TIMES consists in the fact that it provides insights on how modal shift occurs in the different types of residential location and for diverse consumer groups. This new insight enabled by the model is particularly valuable, as it allows to design more effective and efficient policies encouraging the transition to a fossil-free transportation sector. On the one hand, MoCho-TIMES identifies the consumers groups more willing to shift towards zero- and low-carbon modes, thus allowing to establish priorities. On the other hand, the novel approach supports the understanding of the most suitable policy levers to target the different consumers groups. The results in Section 4.1 show that a shift away from car transport is more likely to happen in urban and suburban areas rather than in rural ones, which are less served by public transport. Moreover, lower income classes seem more willing to shift away from car transport. Finally, the analysis of the trend of CO₂ emissions of the alternative scenarios points out that regulation and active participation of the Government in transport planning are fundamental to promote a paradigmatic shift in transport and to encourage the sustainable transition. The results of the model suggest that providing alternatives to car for traveling, building new infrastructures, improving the LoS and the accessibility to public transport, especially in rural areas, and setting up an effective taxation and incentive scheme are measures of primary importance to lead the transition of transport towards sustainability.

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Appendix A

Table 1
Assumptions for the scenario analysis: (L: Urban, S: Suburban, R: Rural, BEV: Battery electric vehicle, FCEV: Fuel cell electric vehicle, PHEV: Plug-in electric vehicle).

	BAU	HUA-HII	HUA-LOI	LOA-LOI	LOA-HII
Infrastructure [Mpkm]	Bike infrastructure	5190	5190	2595	2595
	Metro infrastructure	706	706	586	586
	S-train infrastructure	1445	1651	1445	1445
	Train infrastructure	4957	6357	4957	4957
	Road infrastructure	72,385	71,088	79,624	79,624
Ticket and parking price [MDKK/Mpkm]	Ticket driver until 2020	0.01	0.01	0.01	0.01
	Parking driver until 2020	0.01	0.01	0.01	0.01
	Ticket driver after 2020	0.01	–0.01	0.015	0.015
	Parking driver after 2020	0.01 U/S/R	0.015 U, 0.012 S/R	0.01 U/S/R	0.01 U/S/R
	Tax on diesel after 2020	74.4 constant	81.8 + 3% yearly	74.4 constant	74.4 constant
Fuel tax [MDKK/PJ]	Tax on gasoline after 2020	127.7 constant	134.1 + 1% yearly	127.7 constant	127.7 constant
	Tax on natural gas after 2020	54.3 constant	57 + 2% yearly	51.6 constant	51.6 constant
	Tax on electricity after 2020	246.7 constant	0	246.7 constant	246.7 constant
	VRT on fossil fuelled cars after 2020	Payable VRT (105% until 98,510 DKK and 150% above that)	105% until 80,000 DKK and 180% above that	Payable VRT	Payable VRT
	VRT on BEV after 2020	Payable VRT	0	Payable VRT	Payable VRT
Vehicle registration tax (VRT) [MDKK/kvehcle]	VRT on FCEV after 2020	VRT is introduced gradually, multiplying by 0.4 in 2020, 0.65 in 2021, 0.9 in 2022 and 1 in 2023	20% of payable VRT	VRT is introduced gradually, multiplying by 0.4 in 2020, 0.65 in 2021, 0.9 in 2022 and 1 in 2023	VRT is introduced gradually, multiplying by 0.4 in 2020, 0.65 in 2021, 0.9 in 2022 and 1 in 2023
	VRT on PHEV after 2020	Payable VRT	20% of payable VRT	Payable VRT	Payable VRT
	VRT on diesel bus	60% above 11,968 DKK	100% above 11,968 DKK	60% above 11,968 DKK	60% above 11,968 DKK
	Travel Time Budget after 2020	1696 Mbs in 2010, 2217 Mbs in 2050	BaU*1.1	BaU*0.95	BaU*1.1
	Perception	Car congestion time penalty factor	3	1	3
TTB [Million hours]	Car ferry time penalty factor	0.75	1.5	0.75	1.5
	Car ferry wait penalty factor	0.3	3	0.5	3
	PT waiting time penalty factor	1.5	1.2	2	1.2
	PT walking time penalty factor	1.5	1.2	2	1.2
	Bike attractiveness	0	0.03	0	0.03
	Walk attractiveness	0	0.13	0	0.13
	Multiplier VoT	1	0.9	1.1	0.9

(continued on next page)

Table 1 (continued)

Level of service	BaU	HIA-HII	HIA-LOI	LOA-LOI	LOA-HII
Car speed multiplier	1	0.85 U, 0.95 S/R	0.85 U, 0.95 S/R	1.2 U, 1.1 S/R	1.2 U, 1.1 S/R
Car congestion time	1	1.1 U, 1.05 S/R	1.1 U, 1.05 S/R	0.9 U/S/R	0.9 U/S/R
Train speed multiplier	1	1.05 U, 1.1 S, 1.15 R	1.05 U, 1.1 S, 1.15 R	1 U/S/R	1 U/S/R
Train walking time	1	0.95 U, 0.9 S/R	0.95 U, 0.9 S/R	1 U/S/R	1 U/S/R
Train waiting time	1	0.95 U, 0.9 S/R	0.95 U, 0.9 S/R	1 U/S/R	1 U/S/R
Train departure waiting time multiplier	1	0.95 U, 0.9 S/R	0.95 U, 0.9 S/R	1 U/S/R	1 U/S/R
S-train speed multiplier	1	1.2 U, 1.1 S/R	1.2 U, 1.1 S/R	1 U/S/R	1 U/S/R
S-train walking time	1	0.85 U, 0.9 S/R	0.85 U, 0.9 S/R	1 U/S/R	1 U/S/R
S-train waiting time	1	0.85 U, 0.95 S/R	0.85 U, 0.95 S/R	1 U/S/R	1 U/S/R
S-train departure waiting time multiplier	1	0.85 U, 0.95 S/R	0.85 U, 0.95 S/R	1 U/S/R	1 U/S/R
Metro speed multiplier	1	1.2 U, 1 S/R	1.2 U, 1 S/R	1 U/S/R	1 U/S/R
Metro walking time	1	0.8 U/S, 0.95 R	0.8 U/S, 0.95 R	1 U/S/R	1 U/S/R
Metro waiting time	1	0.8 U, 0.95 S/R	0.8 U, 0.95 S/R	1 U/S/R	1 U/S/R
Metro departure waiting time multiplier	1	0.8 U, 0.95 S/R	0.8 U, 0.95 S/R	1 U/S/R	1 U/S/R
Bus speed multiplier	1	1.2 U, 1.1 S/R	1.2 U, 1.1 S/R	1.05 U/S/R	1.05 U/S/R
Bus walking time	1	0.85 U, 0.9 S/R	0.85 U, 0.9 S/R	1 U, 0.97 S/R	0 U, 0.97 S/R
Bus waiting time	1	0.95 U/S/R	0.95 U/S/R	0.97 U/S/R	0.97 U/S/R
Bus departure waiting time multiplier	1	0.95 U/S/R	0.95 U/S/R	0.97 U/S/R	0.97 U/S/R
Bike speed multiplier	1	1.2 U, 1.1 S/R	1.2 U, 1.1 S/R	1 U/S/R	1 U/S/R
Walk speed multiplier	1	1.55 U/R, 1.45 S	1.55 U/R, 1.45 S	1 U/S/R	1 U/S/R

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Glossary

<i>ASC</i> : Alternative-specific constants	<i>E4</i> : Energy-economy-environment-engineering
<i>AFV</i> : Alternative fuelled vehicles	<i>ETSAP</i> : Energy Technology Systems Analysis Program
<i>BaU</i> : Business as Usual scenario	<i>FCEV</i> : Fuel cell electric vehicles
<i>BY</i> : Base year	<i>GDP</i> : Gross domestic product
<i>BEV</i> : Battery electric vehicles	<i>GHG</i> : Greenhouse gas
<i>BU</i> : Bottom-up	<i>H</i> : High income level
<i>CSTDm</i> : California Statewide Travel Demand Model	<i>HIA-HI</i> : High Authority commitment – High Individual commitment
<i>CG</i> : Consumer group	<i>HIA-LOI</i> : High Authority commitment – Low Individual commitment
<i>DKK</i> : Danish Kroner	<i>IEA</i> : International Energy Agency
<i>DKE</i> : Denmark East	<i>LoS</i> : Level-of-service
<i>DKW</i> : Denmark West	<i>LTM</i> : Landstrafikmodellen, Danish National Transport Model
	<i>L</i> : Low income level
	<i>LOA-HI</i> : Low Authority commitment – High Individual commitment
	<i>LOA-LOI</i> : Low Authority commitment – Low Individual commitment
	<i>M</i> : Medium income level
	<i>Mpkm</i> : Million-passenger kilometres
	<i>MNL</i> : Multinomial logit model
	<i>MoCho-TIMES</i> : Modal Choice in TIMES
	<i>NMNL</i> : Nested logit model
	<i>OD</i> : Origin-destination
	<i>OECD</i> : Organisation for economic co-operation and development
	<i>PHEV</i> : Plug-in hybrid
	<i>RMS</i> : Regional Modeling System
	<i>TIMES</i> : The Integrated Markal Ecom System
	<i>TTB</i> : Travel time budget
	<i>TU</i> : The Danish National Travel Survey
	<i>VL</i> : Very low income level
	<i>VoT</i> : Value of time
	<i>VRT</i> : Vehicle registration tax

**MODELLING TRANSPORT MODAL
SHIFT IN TIMES MODELS
THROUGH ELASTICITIES OF
SUBSTITUTION**



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Modelling transport modal shift in TIMES models through elasticities of substitution

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HIGHLIGHTS

- Novel methodology to endogenise modal shift in energy system models.
- Substitution elasticities are adopted to regulate transport modal shares.
- Modal demands self-adjust elastically in response to shadow price changes.
- Sensitivity analysis on elasticities reveals substitution saturation.
- Interactions between novel methodology and traditional model structure explained.

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ABSTRACT

Several efforts have been directed lately towards the endogenisation of transport modes competition in Energy/Economy/Environment/Engineering (E4) models. TIMES-DKEMS is a novel methodology paving the way for applying elasticities of substitution to incorporate transport modal shift into TIMES (The Integrated MARKAL-EFOM System) models. Substitution elasticities are defined for four transport demand aggregates, each corresponding to a different distance range class. Within an aggregate, modal demands can adjust their levels according to the defined substitution elasticity and in response to changes of their shadow prices relative to a reference case. The total volume of the transport demand over the aggregate is conserved and modal shift potentials are implemented to guarantee realistic dynamics. The behavior of TIMES-DKEMS is tested under an arbitrary environmental policy, an increasingly stringent bound on CO₂ emissions. Modal shares are compared with the standard version of TIMES-DK. Results show that in 2050, 11% of car mobility demand is substituted by more efficient and less costly modes such as train and coach. A sensitivity analysis on the values of substitution elasticities indicates that higher absolute values correspond to larger modal shift. Finally, other model constraints, such as mode-specific travel patterns, interact with the substitution mechanism resulting in a modal shift containment.

1. Introduction

Transport is a key driver and key enabler of economic growth and plays a fundamental role in supporting quality of life. However, it is also responsible for approximately 28% of total final energy use and for 23% of the world energy-related CO₂ emissions [1]. It is the sector that experienced the highest growth in emissions since 1990, and presents the least diversified portfolio of energy supply sources, relying mainly on petroleum products [2]. Transport is widely considered the most complicated energy sector to decarbonise, due to multiple reasons.

Transportation activity is strongly coupled with gross domestic product (GDP), incomes and population levels, which are increasing factors for most countries [3]. Mobility demand per capita in countries outside the Organisation for Economic Co-operation and Development (OECD) is still below the levels of OECD countries, but is expected to grow at a faster pace. Some low-carbon transport technologies have appeared in the market [4], but their high upfront costs still hamper a wide adoption, thus making policy support still a requirement to enhance their acceptability [5,6]. Moreover, the uptake of new transportation technologies is slowed down by the slow turnover rate of the existing

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Nomenclature		t	year index ($t = 2010, \dots, 2050$)
Variables		Superscripts	
DM_k	demand aggregate [Mpkm]	o	reference case
$DM_{k,i}$	modal demand segment [Mpkm]	\cdot	after substitution
$sm_{k,j,l}$	modal demand segment step variable in the low direction [Mpkm]	Glossary	
$sm_{k,j,l}$	modal demand segment step variable in the up direction [Mpkm]	BU	bottom-up
$zm_{j,k}$	aggregate demand step variable in the low direction [Mpkm]	BY	base year
$zm_{j,k}$	aggregate demand step variable in the up direction [Mpkm]	CES	constant elasticity of substitution
$P_{k,i}$	modal demand segment shadow price [M Danish Kr./Mpkm]	CO ₂	carbon dioxide
		DKE	Denmark east
		DKW	Denmark west
		E4	energy-economy-environment-engineering
		ETSAP	Energy Technology Systems Analysis Program
		GDP	gross domestic product
		GHG	greenhouse gas
		H	hybrid
		ICE	internal combustion engine
		IEA	International Energy Agency
		L	long distance
		LTM	Landstrafikmodellen, Danish National Transport Model
		M	medium distance
		MNL	multinomial logit
		O&M	operation and maintenance
		OECD	Organisation for Economic Co-operation and Development
		Pkm	Passenger-kilometre
		S	short distance
		TD	top-down
		TIMES	The Integrated Markal Ecom System
		TIMES-DK	TIMES model of Denmark
		TIMES-DKEMS	TIMES model of Denmark with Elastic Modal Shift
		TIMES-DKMS	TIMES model of Denmark with Modal Shift
		Tkm	Tonne-kilometre
		TU	The Danish National Travel Survey
		XS	extra short distance
Parameters			
$DM_{k,i}^0$	modal demand segment in the reference case [Mpkm]		
α_k	elasticity of substitution [–]		
$\Delta_{k,i}^{lo}$	modal shift potential in the low direction [%]		
$\Delta_{k,i}^{up}$	modal shift potential in the up direction [%]		
$\beta_{k,i}$	step variable width [Mpkm]		
$P_{k,i}^-$	demand decrease price function coefficients [M Danish Kr./Mpkm]		
$P_{k,i}^+$	demand increase price function coefficients [M Danish Kr./Mpkm]		
$\delta_{i,k}$	user-defined substitution rate [–]		
m	number of linearization step in the low direction [–]		
n	number of linearization step in the up direction [–]		
N_k	number of component demands composing the aggregate [–]		
Indices			
k	aggregate index ($k = XS, S, M, L$)		
j	linearization step index ($j = 1, \dots, m; n$)		
i	component demand index ($i = 1, \dots, N_k$)		

vehicle fleet and the lock-in effect originated by the existing infrastructure. So far, efforts to reduce transport emissions through technological improvements and fuel standards have been offset by the increase of activity. The International Energy Agency (IEA) estimates in its baseline scenario an increase of nearly 75% in global transport energy consumption by 2050 and almost a doubling of associated CO₂ emissions worldwide [7]. IEA suggests a combination of three technological and behavioral measures to be promoted concurrently: avoiding travel, shifting to different modes and improving vehicle efficiency [2,7]. Another set of measures recommended includes development of efficient technologies, changes in pricing and budgeting, attitudinal change, infrastructure supply, innovative institutional arrangements and development of new methods [8]. Therefore, it is widely recognized that the behavioral dimension is central to leading the transition to a low-carbon transportation sector.

Energy system models are powerful tools for supporting long-term decision making in the energy sector. In this study we focus on a specific family of them, the TIMES models, belonging to the category of energy-economy-environmental-engineering (E4) optimization models. TIMES models have been used for more than three decades to identify least-cost resources and technology deployment pathways towards greenhouse gas (GHG) emission-free energy systems, exploring alternative scenarios under several constraints and for different countries such as Ireland [9], California [10,11], Canada [12], China [13] or even globally [14]. E4 models stand for their detailed representation of the

technological, economic and environmental dimensions of the integrated energy system and their capability to explore decarbonisation pathways, considering cross-sectoral dynamics and synergies. Nonetheless, E4 models are still weak at depicting human behavior driving consumer's choice [15,16]. Since individuals' preferences are a fundamental aspect of decision-making in the transportation sector, the behavioral dimension should be embedded in E4 models to depict real households' behavior and their preferences towards modal choice and use of transportation technologies [17]. This study moves a step forward in the representation of behavior in transport in energy system models proposing TIMES-DKEMS, a novel methodology that integrates endogenous modal shift within bottom-up (BU) optimization E4 models through the use of elasticities of substitution. Incorporating endogenous modal shift enables the direct assessment of its potential contribution to a low carbon future energy system, allowing dedicated policy analysis. This study reviews the modeling of modal choice in transport and energy system models in Section 2. Section 3 describes the approach of TIMES-DKEMS in all its aspects. The results for a Baseline scenario and for the sensitivity scenarios are analyzed in Section 4, which also provides some insights on the new capabilities of the model. Section 5 discusses the main advantages and shortcomings of the methodology proposed compared to other models in the literature and recommends the direction for future research, aimed at improving the representation of behavior in transport in E4 models. Finally, Section 6 presents the conclusion.

2. Literature review

Modal shift consists of a transfer of mobility demand across modes of transport, as a result of changes in modal choice. Modal choice, in turn, consists of the choice of a mode of transport from two or more alternatives. Considering that modal choice is always among a finite set of mutually exclusive alternatives, this is a typical case of discrete choice problem, which can be represented by discrete choice models, as well described by [18–20]. Transport models have been simulating modal choice for a long time to analyze short and mid-term developments of the transport system of a country, region or city as, for example, in the case of Ireland [21], California [22] and Thailand [23]. Thanks to their highly disaggregated description of the population and their ability to base decisions on many attributes, transport models are valid tools for assessing households' modal choice. On the other hand, in the field of energy system models, the representation of modal choice is an innovative topic. Thanks to the inclusion of simulation methods in the model structure, top-down (TD) [24] and hybrid (H) [25,26] E4 models are able to simulate modal choice through constant elasticities of substitution (CES) and multinomial logit (MNL) functions, which have been used for this purpose for more than four decades, thus being very reliable. Instead, BU optimization energy system models lag behind TD and H models regarding their ability to represent modal shift. Traditional approaches to represent modal choice, e.g. CES and MNL functions, do not fit directly in the optimization framework, (normally based on linear programming). Thus for this class of models, the

research on new modeling techniques for representing modal choice is a cutting-edge topic. A review of the representation of behavior in integrated energy and transport models recognized two main approaches to incorporate behaviorally-realistic modal choice into BU E4 models [15]. The first approach consists of linking the E4 model with an external transport simulation model that incorporates the behavioral features and that determines the modal shares, e.g. through CES [27], MNL functions [28,29], or through elasticities [30]. The second approach consists of determining modal shares directly within the E4 model, by broadening its classical framework to integrate some transport-specific variables relevant to modal choice, such as travel time budget and transport infrastructures [31–33] or modal level of service and consumers' modal perception [34,35]. The methodology developed and presented in this study to integrate modal shift within BU optimization E4 models falls in the second category of such taxonomy. The methodology proposed uses substitution elasticities to mimic modal shift, as described in detail in Section 3. Elasticities are already used to simulate modal shift in TD energy models as in [36,37,24], in H energy models as in [38,25] or in dedicated transport scenario analysis [39]. However, to the authors' knowledge, their application for modal shift modelling in BU optimization models has not been investigated by any existing study in the literature. The present study aims at closing such a gap with TIMES-DKEMS.

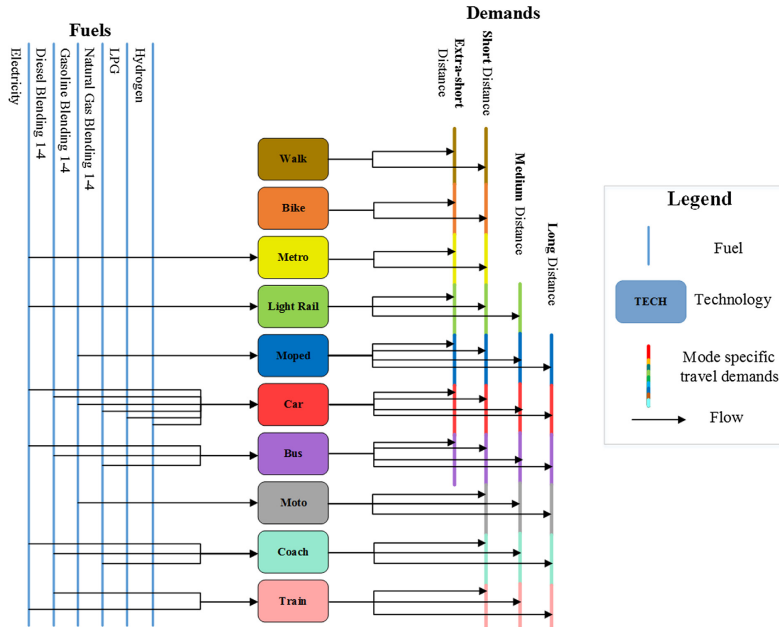


Fig. 1. Standard inland passenger transport sector structure in TIMES-DK. For simplicity, each of the colored segments, representing a portion of each distance range class covered by a specific mode, is represented by the same length. However, the magnitudes of the specific modal demands are usually different. Modified from [31].

3. Methodology

The approach presented in this study allows to incorporate passenger transport modal shift into TIMES models, by using elastic demand functions. While traditionally TIMES models included only the linearized own-price elasticities, recently the elastic demand functions formulation has been generalized, in order to represent elastic substitution among demands by [40]. The approach proposed in this study applies such formulation to simulate transport modal shift. The methodology is developed within the standalone transportation sector of TIMES-DK, the TIMES model representing the complete Danish energy system [41]. This version is called TIMES-DKEMS (TIMES-DK with elastic modal shift).

The full description of the proposed methodology is addressed in the following sub-sections. Section 3.1 introduces the TIMES modelling framework, TIMES-DK and TIMES-DKEMS. Section 3.2 describes the structure of the inland passenger transport sector in TIMES-DK and in TIMES-DKEMS. Section 3.3 describes the use of elasticity of substitution to simulate modal shift endogenously, while Section 3.4 addresses how additional constraints contribute to regulate modal shift. Finally, Section 3.5 defines the scenario used to test TIMES-DKEMS.

3.1. TIMES-DK and TIMES-DKEMS

TIMES (The Integrated MARKAL-EFOM System) model generator is developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP), a Technology Collaboration Programme of the IEA. TIMES models are BU technology-rich energy system models suited for medium/long-term analysis and planning of a national, regional or even city-level energy system. Moreover, TIMES is a techno-economic,

partial equilibrium model generator assuming full foresight and perfectly competitive markets. TIMES models are linear optimization problems whose solution is determined as the minimization of the sum of the total system costs discounted to a reference year, subject to user-defined technological, environmental, resource availability and policy restrictions. The type of inputs used to build TIMES models are typically exogenous service demand curves, supply curves and techno-economic parameters for each technology represented in the model. TIMES outputs are investments, operation and import/export levels, optimal for the energy system as a whole, marginal prices of the energy commodities, emission levels and costs. A detailed description of TIMES is provided by [42].

TIMES-DK is a multi-regional model geographically aggregated into two regions: Denmark East (DKE) and Denmark West (DKW). It is divided into five sectors, viz., supply, power and heat, industry, residential and transport. TIMES-DK is calibrated for the base year (BY) 2010 and has technological and economic projections up to 2050. This time horizon is sub-divided into shorter periods of various duration, most commonly 1–5 years [41]. In turn, every year comprises 32 non-sequential time slices, representing seasonal (4 seasons), weekly (working/non-working days) and daily variations.

TIMES-DKEMS is a lean version of TIMES-DK that represents the Danish transport sector on a standalone basis. A basic supply sector is also included, which describes the international fuel market, but omits most of the production fuel chains (such as hydrogen and electricity). Thus, CO₂ emissions due to electricity generation are not accounted for. TIMES-DKEMS integrates endogenous modal shift only within the inland passenger sector and through elasticities of substitution. The next section describes the differences between the inland passenger transport sector structure in TIMES-DK and TIMES-DKEMS.

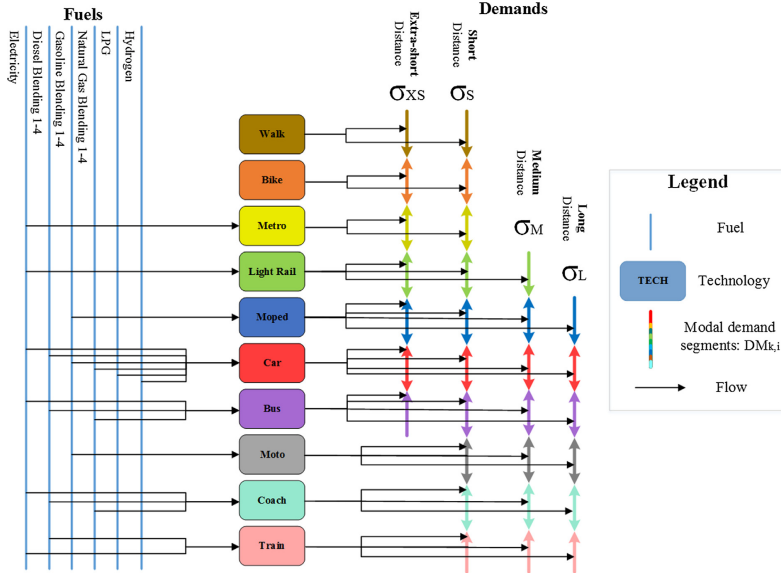


Fig. 2. Inland passenger transport sector structure in TIMES-DKEMS. For simplicity, each of the colored segments, representing a portion of each distance range class covered by a specific mode, is represented by the same length. However, the magnitudes of the specific modal demands are usually different.

3.2. Overview of the inland passenger transport sector in TIMES-DK and TIMES-DKEMS

In TIMES-DK, the transport sector comprehensively describes the Danish mobility service demands, the end-use transport technologies and the technologies producing the transport fuels. The transport sector includes passenger and freight transport, further split into aviation, maritime and inland sub-sectors. The inland passenger sector, which is the focus of this study, includes ten modes: car, bus, coach, rail (metro, train, light rail), 2-wheelers (motorcycle and moped) and non-motorized modes (bike and walk). The mobility service demands are defined exogenously for each mode, from the base year until the end of the modelling horizon. They are expressed as service demands: passenger-kilometer (pkm) and tonne-kilometre (tkm). Moreover, the demands for inland passenger modes are split into four classes of increasing distance range, namely extra short (XS , < 5 km), short (S , 5–25 km), medium (M , 25–50 km) and long (L , > 50 km) (Fig. 1).

The technology database for the transportation sector of TIMES-DK includes existing technologies and technologies that are available for future investments, which compete to meet the projected mobility demands. It is worth noticing that technologies can compete within a mode, but not between modes (i.e. modal shift is not possible, since every transport service demands are exogenously defined for each mode). In addition, competition between transport technologies is exclusively based on costs: TIMES seeks to meet the modal mobility demands with the portfolio of technologies characterized by the lowest leveled costs, while complying with the implemented constraints. Moreover, each mode is constrained to satisfy a specific travel pattern when meeting travel demands. Technologies in a given mode supply demand segments (XS , S , M and L) accordingly to an exogenously defined share, called travel pattern, which reflects population modal travel habits. The travel patterns adopted for the BY are the same as those already described in [31]. Additional flexibility is provided to the model to fulfil the future transport demands, by relaxing travel patterns from 2012 onwards by 2% compared to the BY.

The structure of TIMES-DKEMS allowing elastic inland passenger modal shift is presented in Fig. 2. The main difference between TIMES-DK and TIMES-DKEMS lies in the demand side structure. In TIMES-DKEMS, each distance range class k (where $k = XS, S, M, L$) represents an aggregate, where all corresponding travel demand segments $DM_{k,i}(t)$ (with $i = 1, \dots, N_k$) are grouped together and where a common elasticity of substitution α_k is defined. In this study, the substitution elasticity defined for each aggregate is the same for all the component demands i . Moreover, substitution elasticity could be defined differently among aggregates (see Section 3.3) and for each year t of the time horizon T .

Modal demand segments composing an aggregate k ($DM_{k,i}(t)$) can endogenously adjust their levels in reaction to changes of their shadow prices compared to a reference case. However, each aggregate k is constrained to conserve its total demand after substitution. This latter condition characterizes the so-called volume-preserving variant of substitution elasticities, which is defined in [40]. Modal shift is allowed only from 2020 onwards and only for the inland passenger transport sector.

3.3. Elasticities of substitution

Energy system modelers can adopt elasticities to investigate demand variations in response to price changes driven by alternative scenario assumptions (e.g. fuel prices, availability of resources), or in response to specific set of policy measures (e.g. emission taxes, emission cap, etc.). The adoption of elastic demand functions in TIMES models requires the definition of a reference case, where the model calculates the reference shadow prices for the relevant demand commodities. In a second moment, the policies under assessment are introduced into the model, which alter the shadow prices of the demand commodities. The model determines a new solution, where the elastic demands re-arrange their

levels because of changes in their shadow prices. The magnitude of the change is regulated by the elasticity value.

Since TIMES models are based on linear programming, the formulation of elasticities of substitution needs to be linearized. Such linearization was developed by [40]. For a specific aggregate k , each of the component demands i can be written as its exogenous value $DM_{k,i}^0(t)$ (identified in the reference case) plus two terms (Eq. (1)). Each of these terms represents a set of step variables used to rearrange the demand level in response to elastic price changes [40].

$$DM_{k,i}(t) = DM_{k,i}^0(t) - \sum_{j=1}^n sm_{k,j,i}(t) + \sum_{j=1}^m sn_{k,j,i}(t) \quad (1)$$

In each year t , each step variable $sm_{k,j,i}(t)$ and $sn_{k,j,i}(t)$ are bounded between zero and a width $\beta_{k,j,i}(t)$, where n and m (indexed by j) are the steps used to linearize the elastic response in the up and low direction respectively. Moreover, demand variation is limited, upwards and downwards, by a maximum percentage change $\Delta_{k,i}^{up}(t)$ and $\Delta_{k,i}^{lo}(t)$ declared relative to $DM_{k,i}^0(t)$. Therefore, defining n , m and $\Delta_{k,i}^{up,lo}(t)$ identifies the width $\beta_{k,j,i}(t)$ of each step, assuming that the aggregate demand remains at the reference value.

The demand price functions of the step variables are included in the objective function, and their coefficients are expressed by $p_{k,j,i}^\pm(t)$ (Eq. (2)). For every demand i , each increase and decrease step has a price associated, which depends on the step itself (j), the elasticity of substitution declared for the aggregate α_k , the exogenous demand component $DM_{k,i}^0(t)$ and the shadow price obtained from the reference case $p_{k,i}^0(t)$.

$$p_{k,j,i}^\pm(t) = p_{k,i}^0(t) \left(\frac{DM_{k,i}^0(t) \pm (j - \frac{1}{2}) \cdot \beta_{k,j,i}(t)}{DM_{k,i}^0(t)} \right)^{\frac{1}{\alpha_k}} \quad (2)$$

Moreover, an ulterior condition is required for having the aggregate volume preserved after substitution; such condition can be expressed as follows (Eq. (3)):

$$\begin{aligned} DM_k'(t) &= \sum_{i=1}^{N_k} \delta_{i,k}(t) \cdot DM_{k,i}(t) = \sum_{i=1}^{N_k} \delta_{i,k}(t) \cdot DM_{k,i}^0(t) - \sum_{j=1}^n \sum_{i=1}^{N_k} \mathcal{Z}_{m,j,k}(t) \\ &\quad + \sum_{j=1}^m \sum_{i=1}^{N_k} \mathcal{Z}_{n,j,k}(t) \\ &= DM_k^0(t) - \sum_{j=1}^n \mathcal{Z}_{m,j,k}(t) + \sum_{j=1}^m \mathcal{Z}_{n,j,k}(t); \quad \forall t \in T \end{aligned} \quad (3)$$

where $DM_k^0(t)$ and $DM_k'(t)$ are the weighted sums of the N_k component demands composing the aggregate k before and after substitution respectively and $\delta_{i,k}(t)$ are user-defined substitution rates between component i and aggregate k (which in the simplest case may all be assumed equal to 1). The terms $\mathcal{Z}_{m,j,k}(t)$ and $\mathcal{Z}_{n,j,k}(t)$ are the step variables used to linearize the elastic response of the aggregate demand relative to its own-price variation.

In this study, the own-price elasticities for all aggregates k are assumed null, and substitution rates between component demands $\delta_{i,k}(t)$ are all assumed unitary. In particular, the latter assumption is necessary to guarantee that the demand substitution retains the physical volume, e.g. forcing 1 pkm of rail transport to be substituted for each pkm of car transport [40]. In this specific case, Eq. (3) reduces to Eq. (4):

$$DM_k'(t) = \sum_{i=1}^{N_k} DM_{k,i}(t) = \sum_{i=1}^{N_k} DM_{k,i}^0(t) = DM_k^0(t); \quad \forall t \in T \quad (4)$$

The model determines the new levels of component demands $DM_{k,i}(t)$ by means of maximizing the total surplus of consumers and producers represented in the system, while fulfilling all the constraints defined in the model.

3.4. Shift potentials

The shift potential is a constraint that limits the maximum and

minimum demand that each mode can satisfy for each year of the time horizon and for each distance range class k . In TIMES-DKEMS, for a specific year t , each demand segment $DM_{k,i}(t)$ composing an aggregate k can re-adjust its level compared to its original exogenous value $DM_{k,i}^0(t)$ in both directions up or low, by a maximum percentage $\Delta_{k,i}^{up,lb}(t)$ (Eq. (5)):

$$DM_{k,i}^0(t) - \Delta_{k,i}^{lb}(t) \cdot DM_{k,i}^0(t) \leq DM_{k,i}(t) \leq DM_{k,i}^0(t) + \Delta_{k,i}^{up}(t) \cdot DM_{k,i}^0(t) \quad (5)$$

Given the mathematical structure of the elastic demand formulation adopted for TIMES-DKEMS [40], the maximum technical variation for a specific $DM_{k,i}(t)$ is obtained when a 100% potential is assumed.

The shift potentials adopted for each demand segment $DM_{k,i}(t)$ are based on [31], where estimations are provided on the basis of the modal trip distance profiles extracted by the Danish National Travel survey (TU survey) [43]. In 2050, the different demand segments (XS, S, M and L) supplied by a specific mode are limited above by the sum of the transport demands that can shift out from all the other modes within the same distance range classes. Since the maximum shift potentials identified in [31] for 2050 exceeds the technical bound allowed by the elastic demand formulation for each demand segment, the maximum demand segment increase $\Delta_{k,i}^{up}(t)$ for each mode and each distance range class in 2050 is set up to 100% as outlined in Table 1. The only exception is represented by car, whose upward demand variations are set to zero for each k and for the entire time horizon. Such choice is adopted in order to be in line with other studies which address the same topic, and whose research question is the estimation of modal shift away from cars towards other modes [31,33].

The shift potentials in the low direction $\Delta_{k,i}^{lb}(t)$ are calculated similarly to the upward case, and are also based on [31]. In 2050, they are estimated assuming a complete shift from a specific mode towards all the others compatible with its distance range class and assuming a full shift. In most of the cases, the estimations found by [31] show a potential complete shift of each demand segment. For this reason, the maximum demand segment decrease assumed for each $DM_{k,i}(t)$ in 2050 is set up to -100% (Table 1). The only exceptions are the long distance coach demand and the long distance train demand, whose maximum decrease variation estimation is 87% and 86% respectively. Lastly, in 2020, the upper and lower bound for each demand segment variation is obtained assuming a null potential in 2010 and interpolating linearly the potential defined in 2050 within the whole time horizon.

The maximum modal shifts achievable in each distance range class k are presented in Table 2. Since the aggregate demand is constrained to remain constant before and after substitution, the net total demand change is null. For this reason, the maximum modal shift achievable is calculated as how much of the highest contribution to the shift among the modes in the aggregate ($\Delta_{k,i}^{up,lb}(t) \cdot DM_{k,i}^0(t)$) can be accommodated among the rest of the component demands, given their shift potentials and according to the variation direction. In TIMES-DKEMS, the highest contributor to the shift potential in every distance range class is car, which can only decrease. Values shown in Table 2 represent how much of this demand can be accommodated in the rest of the demand segments.

3.5. Scenario description

The use of elasticities of substitution to simulate modal shift in TIMES models is hereby tested by comparing the results obtained with the standalone transportation sector of TIMES-DK (from now on simply called TIMES-DK) and TIMES-DKEMS (described in the previous sections). The two models are identical in terms of dataset describing the technological and economic parameters of transport technologies and they differ only in terms of transport demand structure, as already explained in Section 3.2 and visible comparing Figs. 1 and 2.

The two model results are compared for the same Baseline scenario, which includes an increasingly stringent bound on CO₂ emissions acting

from 2020 up to the end of the time horizon (Table 3).

The elasticity of substitution values adopted for the Baseline scenario σ_k are set equal to -3 for each t and each aggregate k . Moreover, for each demand segment, 10 step variables are used to linearize its elastic response in both the up (n) and the low direction (m), within each t . Lastly, elastic substitution is allowed only from 2020 onwards with an increasing potential, as outlined in Section 3.4.

The choice of the policy measure is arbitrary and has the sole scope of stimulating changes in the shadow prices of the transport demand segments in TIMES-DKEMS compared to the reference case. These changes in shadow prices drive the demands elastic responses. Nevertheless, the CO₂ emission-bound trend is obtained from the CO₂ emissions trajectory resulting in [31] when allowing endogenous modal shift in TIMES-DK. This choice is done to facilitate comparison with a similar case study. Reference shadow prices $p_{k,i}^0(t)$ are calculated by letting the model find the optimal solution without the environmental constraint under study and without elastic demand functions, *ceteris paribus*.

4. Results

This section provides the results of the analysis undertaken to test the use of substitution elasticities to model modal shift in TIMES models. First, Section 4.1 compares the results obtained with TIMES-DK and TIMES-DKEMS for the Baseline scenario. In Section 4.2, a sensitivity analysis is conducted on TIMES-DKEMS to assess how modal substitution is affected by a variation in the assumed elasticities.

4.1. Elastic modal shift results

The modal shares determined by TIMES-DKEMS in 2050 are compared to the ones exogenously declared in TIMES-DK in Fig. 3. In TIMES-DK the optimal solution is the least-cost fleet of technologies that satisfies the exogenously defined transport demand segments ($DM_{k,i}^0(t)$) for the entire time horizon. On the other hand, in TIMES-DKEMS, the solution is determined as a co-optimization of modal shares and technology shares, providing the model with extra flexibility in the identification of least-cost decarbonisation pathways. TIMES-DKEMS can fulfil the environmental target also shifting part of the mobility demand from one transport mode to another; in particular, this occurs only when this choice is beneficial from a total system cost perspective, resulting in a lower total expenditure for the entire time horizon compared to TIMES-DK.

In TIMES-DKEMS, train, coach, light rail and metro increase their demands compared to their exogenous defined levels (represented by TIMES-DK demand levels) at the expense of car and bus, while the demands of the other modes remain almost constant. In particular, given their travel patterns, coach and train substitute car and bus in the longer distance classes, while light rail and metro in the lower ones. The highest overall contribution to modal shift is due to mode car, whose demand decreases by almost 11% compared to its original level. Car transport is mostly replaced by train and coach, modes with lower levelized costs, which increase their demands by respectively about 96% and 47% compared to TIMES-DK.

Table 1

Modal shift potentials $\Delta_{k,i}^{up,lb}(t)$ for each mode. The adopted potentials are equal across distance range class k . Other modes include: public bus, coach, motorbike, moped, light rail, train, metro, bike and walk. * Long distance demand segments for coach and train have 87% and 86% low potential respectively in 2050.

Year	2020	2050
Car	-25%; +0%	-100%; +0%
Other modes*	-25%; +25%	-100%; +100%

Table 2
Maximum achievable modal shift (Mpkm) in each aggregate k . The total is the sum across the aggregates.

	Aggregate (k)	Year	
		2020	2050
Maximum achievable modal shift (Mpkm)	XS	637	2617
	S	1102	5542
	M	595	2578
	L	1747	7466
	Total	4081	18,203

Table 3
Bound on CO₂ emissions over the time horizon (Baseline scenario).

Year	2020	2025	2030	2035	2040	2045	2050
CO ₂ emission bound (Mtonnes)	10	7.5	6.5	5.8	5	4.5	0

Modal shift is shown in greater detail in Fig. 4, where changes in demands are presented for the entire time horizon in both absolute values and as percentage of maximum achievable modal shift in 2050 (shown in Table 2). Moreover, modal shift is presented separately for each distance range class k , and as total (Tot) summing up all contributions across classes.

The highest contributor to the overall modal shift (Tot) among distance range classes, is represented by the long distance (L), which provides the largest response in terms of elastic demands change. The explanation for this behavior is in the magnitude of each demand aggregate k defined exogenously. As explained in Section 3, transport demand segments can change their levels only in relation to their exogenous values $DM_k^0(t)$, and by a theoretical maximum change of $\pm 100\%$, thus larger demand segments can vary more than smaller demand segments. The long distance aggregate (L) covers the largest share of the overall transport demand in Denmark in each year with a

42% share, thus it is also the distance range class responsible for the highest shift in demand. Concerning the other distance range classes S , M and XS , they cover each year 30%, 20% and 8% of the total transport demand respectively. The same merit order is roughly respected also for contributions to the overall modal shift.

The total modal shift increases over the time horizon, covering in 2020 15% of the maximum achievable shift and reaching 44% in 2050. This increasing trend is the result of a combined effect: the increasing relaxation of the shift potential for each demand segment over the time horizon (shown in Table 1), and an increasingly stringent bound on CO₂ emissions over the same period. The only exception to this behavior is identified in the lower distance classes. Within XS and S , modal shift shows an initial increase culminating in 2025, to which follows a slight decrease. For XS , this trend continues until the end of the time horizon, while for S , it translates into a plateau. The mentioned trends can be explained considering that the S and XS distance range classes have the highest concentration of zero-emission modes already in 2020, such as walk, bike, metro and light rail (only present in XS and S) and light rail. For this reason, at the early stage of the time horizon (2020 – 2025), when alternatives with lower carbon emissions are still not fully available for cars, the model fully exploits the availability of such options already accessible for other modes, substituting car demands in XS and S with walk, bike, metro, light rail and train, until saturating their shift potentials for such years. In the second part of the time horizon, when the CO₂ bound becomes more stringent and clean technologies available in the rest of the distance range classes, modal shift dominates in the longer distance classes.

As expected, modal shift also affects fuel consumption. The evolution of fuel consumption from inland passenger transport sector over the time horizon is provided for the two models in Fig. 5, together with the applied bound on CO₂ emissions. TIMES-DK and TIMES-DKEMS are characterized by similar patterns for total fuel demand and their composition. Fossil fuels are gradually substituted by bio-fuels and electricity, as a result of the increasingly stringent emissions bound (emissions for such energy vectors are not accounted for).

In both the models, the total fuel demand decreases over time,

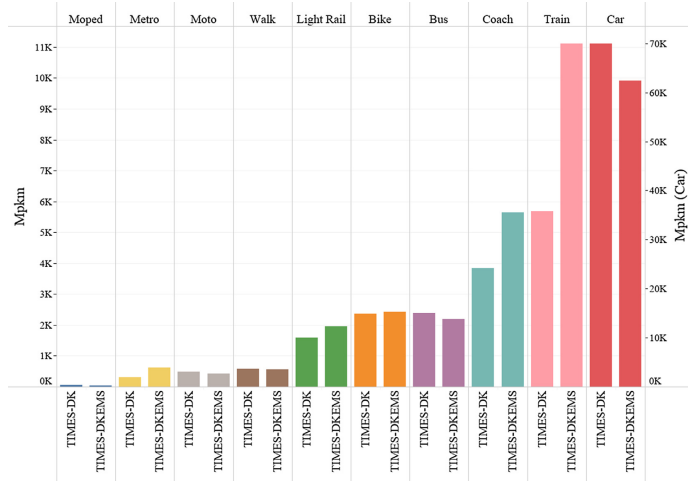


Fig. 3. Comparison of the modal shares in 2050 for TIMES-DK and TIMES-DKEMS.

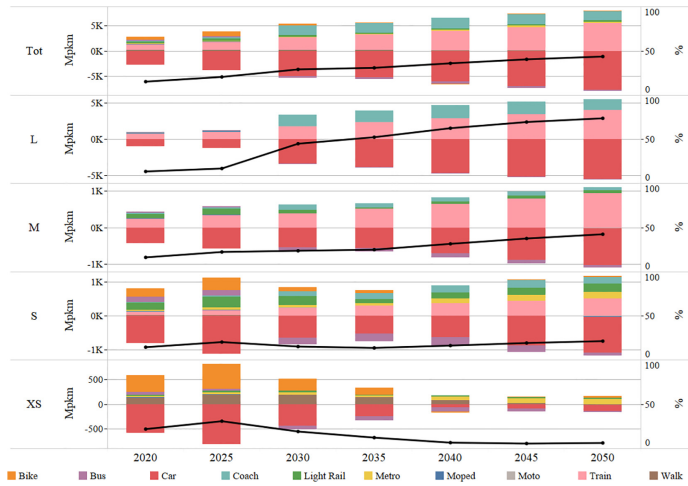


Fig. 4. Modal shift in TIMES-DKEMS.

despite the increasing transport activity. This is due to the combination of increasing fuel economy for new vehicles and a slight electrification of the fleet (electric vehicles have a significantly higher fuel economy than their equivalent internal combustion engines (ICE)). However, the two models show increasing differences in terms of fuel consumption in the period when the environmental constraint is active. In particular, TIMES-DKEMS is characterized every year by a lower final energy

demand, which in 2050 accounts for 12 PJ less than TIMES-DK, representing a 12.5% of fuel saving. These differences are attributable to modal shift, which in 2050 occurs mostly away from car towards the more efficient modes, viz., train and coach (Fig. 3).

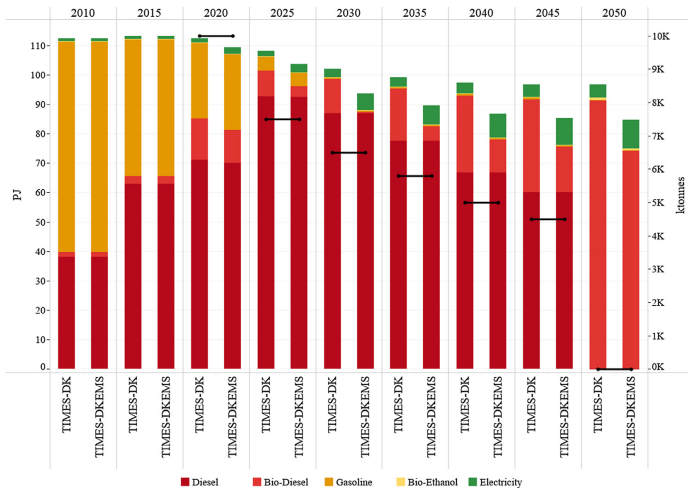


Fig. 5. Fuel consumption in inland passenger transport sector and CO₂ bound for TIMES-DK and TIMES-DKEMS in the Baseline scenario.

4.2. Sensitivity analysis

This section analyses the sensitivity of TIMES-DKEMS to the main parameter involved in regulating the substitution mechanism, which is σ_k , with respect to the Baseline scenario and in terms of modal shift. The value of the substitution elasticity is varied in the range of -1 and -5 and is assumed equal for all the aggregates k and for each year t of the time horizon.

Total modal shift in the inland passenger transport sector resulting from the different values adopted for σ_k is shown in Fig. 6. Across all the different sensitivity cases analyzed, modal substitution dynamics are characterized by a pattern similar to the one already identified and explained for the Baseline case (see Section 4.1). For all the values of σ_k adopted, total modal shift increases steadily over the years. As for the Baseline scenario, this is the result of a combined effect of the increasing emissions bound and the relaxation of shift potentials. The only exception is represented by $\sigma_k = -1$, which shows a higher total modal shift in 2030 compared to 2050. This can be explained considering that 2035 is a model transition year, when most of the clean technologies become available and more competitive for every mode compared to previous years. Thus in 2030, when such options are not yet available, for some modes, the model prefers shifting part of the modal demand, instead of adopting specific modal technologies. This phenomenon is evident only for $\sigma_k = -1$ because, for lower elasticities values, the model is less sensitive to changes in shadow prices, thus, the shift takes place only where such difference is more pronounced, namely in 2030. However, besides this year, the trend is also respected for this case.

Higher absolute values of substitution elasticities result in higher levels of modal shift. This trend is verified for each year and for each σ_k (Fig. 6). This behaviour can be explained by elaborating on Eq. (2), which can be written as in Eq. (6) for each year t :

$$p_{k,j,t}^{\pm} = p_{k,j,t}^0 (a_{k,j,t})^{\frac{1}{\sigma_k}} \quad (6)$$

$$\text{where } \begin{cases} a_{k,j,t} > 1 & \text{for } p_{k,j,t}^+ \\ a_{k,j,t} < 1 & \text{for } p_{k,j,t}^- \end{cases} \quad \forall k, \forall j, \forall t$$

In particular, for every j and every i and for $\sigma_k \in (-\infty, 0)$, $p_{k,j,t}^{\pm}$ are monotone functions of σ_k . As shown in Eqs. (7) and (8), $p_{k,j,t}^+$ is a monotone decreasing function of σ_k limited above by $p_{k,j,t}^0$ and below by 0, while $p_{k,j,t}^-$ is a monotone increasing function of σ_k limited below by $p_{k,j,t}^0$:

$$p_{k,j,t}^+ = \begin{cases} p_{k,j,t}^0 & \text{for } \sigma_k \rightarrow -\infty \\ 0 & \text{for } \sigma_k \rightarrow 0^- \end{cases} \quad \forall k, \forall j, \forall t \quad (7)$$

$$p_{k,j,t}^- = \begin{cases} p_{k,j,t}^0 & \text{for } \sigma_k \rightarrow -\infty \\ +\infty & \text{for } \sigma_k \rightarrow 0^- \end{cases} \quad \forall k, \forall j, \forall t \quad (8)$$

The terms $p_{k,j,t}^{\pm}$ are the coefficients of the demand price functions of the increase (+) and decrease (−) step variables that appear in the objective function. In particular, their levels are identified by the model while maximizing the total surplus of consumers and producers in the system. The increase and the decrease of a specific demand segment takes place only when such variation leads to a decrease in the total system cost compared to the inelastic case. This in particular occurs, for the increase, when the price of supplying an additional unit of the i -th demand ($p_{k,i,t}^+$) is lower than $p_{k,i,t}^0$; for the decrease, when the price of supplying an additional unit of demand i -th ($p_{k,i,t}^-$) is higher than $p_{k,i,t}^0$. Since for $\sigma_k \rightarrow -\infty$, $p_{k,j,t}^{\pm}$ tend to $p_{k,j,t}^0$, higher absolute values of σ_k mean the lower the difference between $p_{k,i,t}^+$ and $p_{k,i,t}^0$ and $p_{k,i,t}^0$ should be to make the demand increase and decrease beneficial from a total system cost point of view. Thus, ceteris paribus, increasing σ_k in their absolute values is equivalent to making the model more sensitive to differences between the $p_{k,i,t}^+$ and $p_{k,i,t}^0$.

In addition, higher j corresponds to higher $p_{k,j,t}^-$ and lower $p_{k,j,t}^+$. This means that for higher j , higher differences in shadow prices are needed to trigger a demand change. For this reason, the optimization guarantees that step variables are increased/decreased consecutively and in

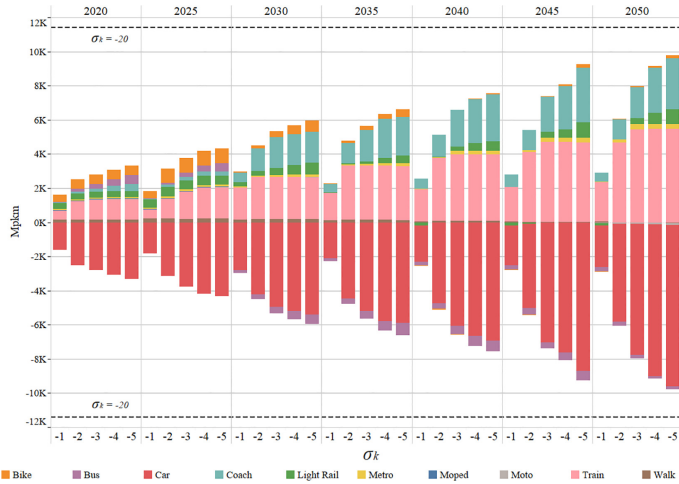


Fig. 6. Total modal shift over the time horizon for different sensitivity cases. Dashed lines represent total modal shift for $\sigma_k = -20$.

the correct order [42]. Thus, higher absolute values of α_k can lead to more step variables being involved in elastic demand response to price change, resulting in a higher demand shift.

On the other hand, the volume preserving condition (Eq. (4)), which forces the net total modal shift to be zero within each aggregate, directly affects the substitution dynamic. Demand segments whose shadow prices have changed enough to stimulate an elastic price demand response, can vary their levels only if other demand components defined in the aggregate vary by the same quantity but in the opposite direction. This can lead, for example, to situations where demand segments increase their levels only to accommodate variations of other demand segments, even though their shadow prices have remained unchanged or have even increased compared to the reference case, representing an additional cost for the system and thus reducing the overall benefit gained by adjusting the other demands in the aggregate. Nevertheless, the overall demand adjustments in an aggregate always bring to an overall increase in the maximized total surplus of consumers and producers compared to the inelastic case.

Total modal shift in 2050 never reaches its maximum achievable (18,203 Mpkkm, Table 2, Section 3.4), but it saturates asymptotically around 11,500 Mpkkm (obtained with $\alpha_k = -20$) (dashed lines in Fig. 6). This can be explained considering the interaction between the substitution mechanism and the travel patterns, which results in a distortion of the elastic demand response dynamic explained above. Technologies defined in a specific mode are constrained to satisfy a given travel pattern (see Section 3). Moreover, exogenous modal demand segments $DM_{k,i}^0(t)$ across distance range classes follow the same proportions as those outlined by the modal travel pattern. Thus, a modal demand segment variation in a specific distance range class k leads to a different proportion among the demand segments compared to the original one. This results in an impossibility for the marginal modal technology to satisfy the demand variation, unless the variation is counterbalanced by changes (in the same direction) of the other modal demand segments in the other classes k_i , in such a way that their proportions remain constant and equal to the modal travel pattern. However, travel patterns are relaxed by 2% compared to the BY from 2012 onwards, softening this effect.

This latter dynamic hampers modal shift, which saturates asymptotically around 11,500 Mpkkm. After this value, with the set of reference shadow prices $p_{k,i}^0(t)$, and with the specific environmental policy adopted, the model does not gain any ulterior benefit in shifting additional travel demand across the modes, even for higher elasticity values.

5. Discussion and future research

TIMES-DKEMS uses substitution elasticities to model passenger transport modal shift within BU optimization E4 energy system models. Integrating modal shift within energy system models allows to better identify efficient policy mechanisms triggering modal shift towards low-carbon transport modes. The proposed methodology presents a major advantage compared to other approaches aimed at representing the same phenomenon in this type of models, such as [31,32,34]. The data requirement is limited and consists mainly of the identification of the substitution elasticities for the distance range classes α_k , and of the modal shift potentials $\Delta p_{k,i}^{up,lv}(t)$. Contrary to [31,34], the methodology proposed relies only to a minor extent on national travel surveys, while the external support of national transport simulation models is not required. In particular, findings based on the TU survey are used in TIMES-DKEMS only for the identification of modal shift potentials and modal travel patterns. The low data requirement is also reflected by a simple modelling structure (evident from the comparison of Figs. 1 and 2), which relies only on the use of a standard set-up outlined in [40] that avoids the definition of ulterior constraints and makes the modelling structure straightforward and compact. However, this study did not account for transport infrastructure, like road and rail networks,

which are necessary requirements to accommodate travel demand. In particular, modal shift could be limited by infrastructure saturation as considered by [31]. The inclusion of such aspect in TIMES-DKEMS would lead to a more complex modelling structure than the one outlined.

The major drawback of using substitution elasticities for simulating modal shift is the severe simplification of the addressed phenomenon. In reality, consumer modal choice is driven by multiple factors, such as level of service (LoS) parameters like travel time, travel cost and travel comfort, which characterise every mode differently. Moreover, consumers belonging to different socio-economic and demographic groups (age, gender, income, etc.) evaluate those factors differently, when making transport choices [34]. In the proposed methodology, all these dynamics are reduced to the values adopted for α_k . In addition, the magnitude of modal shift achievable with the methodology hereby presented is limited by its mathematical formulation. In particular, each demand $DM_{k,i}(t)$ can increase or decrease its level by a certain percentage $\Delta p_{k,i}^{up,lv}(t)$ (referred to $DM_{k,i}^0(t)$). This limits the applicability of the methodology only to such cases where modal shift can occur within a 100% change relative to the original travel demands.

The results obtained from TIMES-DKEMS in the Baseline scenario show a similar magnitude and pattern of modal shift as the results obtained in [31]. However, the values of α_k adopted in this study are arbitrary and have the sole aim of illustrating the novel methodology proposed. For the Baseline scenario, the values of α_k were chosen in the light of the sensitivity analyses carried out on α_k . In particular, for $\alpha_k = -3$ the modal shift magnitude obtained is well below the saturation level observed for higher values, and offers a satisfying demand response to changes in the shadow prices obtained with the specific environmental policy applied.

The identification of proper values for α_k is the main challenge for the utilization of elasticities of substitution to simulate modal shift. Transport price elasticities available in the literature, such as those from transport simulation models, cannot be used directly in the novel modelling framework. The reason is that the values of substitution elasticities adopted should always be consistent with the travel costs defined in the model. In TIMES-DKEMS, travel costs for private and public transport modes include annualized investment cost, operation and maintenance (O&M) cost and fuel cost. Instead, transport elasticities available in the literature are usually estimated with respect to different types of costs, which do include O&M costs and fuel cost but could also include, for example, parking fee or road toll for private modes [44,45] and transit fare for public transport [46,47]. Given such differences in travel cost definition, the direct use of transport elasticity values from the literature in TIMES-DKEMS seems a major challenge.

Results shown in Section 4.1 are obtained using the same arbitrary elasticity of substitution α_k for every aggregate k and for the whole time horizon T . Nevertheless, the proposed methodology theoretically allows to differentiate the substitution elasticities across distance-range classes and over time. Moreover, transport price elasticities (such as cross-price elasticities and direct price elasticities) can vary according to trip lengths, as those identified by [46]. Besides, elasticities can also be differentiated with respect to the duration of the response period analyzed, namely short-term and long-term [44,48]. Therefore, future research for the improvement of this methodology will consist of implementing values for the substitution elasticities representative for a real case study and differentiated by distance-range classes and possibly by t . Moreover, a characterization of α_k for every mode i in each aggregate k is theoretically possible with the elastic demand formulations available in TIMES models [40]. This set-up, allowing capturing differences in elastic price response for different modes, could also be tested.

Modal travel patterns tend to hamper the modal shift resulting from the elastic substitution mechanism (Section 4.2). However, travel patterns are included in the model in order to represent modal travel habits, thus, a full exclusion of such constraints would lead to an

unrealistic adoption of transport modes with respect to the distance range classes k . Further research should focus on how more flexible travel patterns than those assumed in this study influence modal shift saturation within TIMES-DKEMS.

Finally, an interesting application of the proposed methodology would be the description of the freight transport modal shift, which is by nature more governed by cost minimization, rather than behavioral aspects. Moreover, the methodology adopted in this study could be applied to describe other phenomena than transport modal shift, where demand substitutions take place with similar dynamics. Additionally, TIMES models offer different variants for substitution elasticities to the volume-preserving assumption used in this study [40], and these can be used for best describing case-specific phenomena.

6. Conclusions

This study presents TIMES-DKEMS, a novel methodology that adopts elasticities of substitution to simulate transport passenger modal shift in TIMES (The Integrated MARKAL-EFOM System) models. Incorporating endogenous modal shift in energy system models enables the assessment of more effective policies encouraging the transition to a fossil-free transport sector, by identifying their interactions with the whole energy system. This is particularly relevant, considering that transport is expected to become increasingly integrated with the rest of the energy system in the future.

The methodology adopted in TIMES-DKEMS is described in detail and tested for an environmental policy stimulating changes in the shadow prices that drive the elastic modal shift. The results show a demand shift towards the more efficient and less carbon-intensive modes defined, increasing over the time horizon as result of the increasingly stringent policy and the increasing shift potentials. Moreover, a sensitivity analysis on the values of the substitution elasticities reveals that higher absolute values of elasticities entail higher modal shift, despite the maximum modal shift potential not being reached. To the contrary, modal shift saturates asymptotically due to the interactions between the substitution mechanism and other model constraints such as the imposition of dedicated travel patterns for the different modes.

The modelling structure is simple and compact, and does not require ulterior constraints definitions in the model. The data requirement is limited to the characterization of the substitution elasticities for each aggregate and of the shift potentials for each demand participating in the elastic response. The main drawback of this methodology consists in the rather simplified representation of modal shift, since all factors driving modal choice in reality are reduced to the values adopted for the substitution elasticities. Moreover, the identification of proper values of elasticities to be adopted seems challenging, considering that transport price elasticities existing in the literature usually account for travel costs different from those usually included in TIMES models. Thus, the authors identify as further research the identification and adoption of substitution elasticities values representative for a real case study, differentiated by distance-range classes, possibly over the time horizon and by mode.

Lastly, the proposed methodology, with the proper adaptations, could be applied in TIMES models to describe phenomena other than transport modal shift, where a demand substitution takes place with similar dynamics.

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PAPER **6**

**ANALYZING EFFECTS OF
TRANSPORT POLICIES ON
TRAVELERS' BEHAVIOUR FOR
MODEL SHIFT IN DENMARK**

Analyzing effects of transport policies on travelers' behaviour for modal shift in Denmark

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**Analyzing effects of transport policies on travelers' behaviour for
modal shift in Denmark**

Abstract

Since transportation demand and modal choice is becoming increasingly dependent on travel costs, the fluctuation of these costs has the potential to affect consumer decisions. In this paper, an agent-based approach is proposed to analyze opportunities for modal shift in Denmark (ABMoS-DK). The mode choice algorithm in ABMoS-DK is based on costs, both tangible (ticket price, fuel price, vehicle taxes, etc.) and intangible (Value of Time (VoT), travel time, level of service, and reliability). The tangible and intangible costs constitute utility of alternative modes and allow us to evaluate the comparative advantages of the alternative modes of transportation. By changing the utilities of modes of transport, modal shift is incentivized within the model. However, due to heterogeneity of consumers, behavioural changes are subject to high degree of uncertainty. Agent Based Modeling and Simulation (ABMS) is capable of simulating the non-linear behavioural aspects of consumers. In ABMoS-DK, a group of travelers with homogeneous characteristics are regarded as agent that make decision in the traffic system according to a series of rational behavioural rules to meet annual extra short, short, medium and long distance travel demands. The characteristics of respondents to the Danish national travel survey are assigned to agents and define the attributes of agents. Each agent follows the mode choice algorithm and decides whether to use non-motorized, public or private transport based on their personal attributes and expectations. A scenario analysis allows us to understand which factors affect the decisions on travel mode choice and how to improve network performance. This paper describes a methodology using Agent Based Modeling in order to simulate the behaviour of commuters based on their socioeconomic characteristics regarding travel mode choice. We find that disincentivizing private cars has the highest potential for shifting from car use followed by incentives for sustainable modes and expansion of infrastructure.

Keywords

Modal shift; transport modes; agent-based; inland transport; Denmark

1. Introduction

The Danish government has adopted the ambitious goal of becoming independent of fossil fuels by 2050 (The official website of Denmark, 2017). While renewable energy is increasingly deployed to meet power and heat demands in Denmark, the transport sector still depends highly on petroleum products and is regarded as the most complicated sector to decarbonize. In 2010, the transportation sector accounted for approximately 23% of energy-related CO₂ emissions worldwide (Sims et al., 2014) and about 36% in Denmark (IEA, 2016), 60% of which are from passenger vehicles (Winther, 2015). The significant challenges faced in moving towards a long-term decarbonization of the transportation sector include the increase of transport demand, lack of available alternatives to fossil fuels, limits to vehicle efficiency, fuel standards and heterogeneity of consumers' behaviour.

The Nordic Energy Technology Perspectives report (IEA, 2016) recommended modal shift as one of the key mechanisms for decarbonizing the energy system in Nordic countries by 2050. Modal shift takes place when one mode has a comparative advantage over another mode (for instance, in the level of service) and promotes a behavioural change in the traveler. Therefore, modal shift is fundamentally a behavioural change: e.g., shifting to non-motorized transport, increasing the occupancy factor of private vehicles, and higher utilization of public transportation. The focus in modal shift is aimed towards travelers, since freight transportation is more constrained, depending on the market trends and policies that are in effect (Baindur and Viegas, 2011).

The transport system is often conceptualized as having three components: vehicles or equipment that move objects (people, goods); guideways or what the vehicles move along; and an operation plan or a set of procedures by which objects and vehicles are moved over guideways (timetables, control systems, etc.) (Boyce, 2005). As such, the factors affecting modal choice are the existing infrastructure, socio-demographic factors and the use of policy tools (Hammadou and Papaix, 2015). However, Barisa (2016) argued that this conceptualization excludes users (and the complexity of their heterogeneous decision-making) from the system.

Energy-Environment-Economic-Engineering (E4) models are tools developed for long-term energy planning and determining least-cost decarbonization pathways (Chiodi et al., 2013; Føyn et al., 2011; McCollum et al., 2012; Yang et al., 2015). Initially, linear

optimization E4 models were limited to representing technology changes and were not able to fully evaluate the influence of behavioural changes on the energy system. Due to the lack of representation of consumers' behaviour in E4 models, the contribution of modal shift to GHG emissions reduction was initially evaluated through "what-if" analyses, which assessed the effect of exogenously assumed levels of transfer of mobility demand from one mode to another on the environment (GEA writing team, 2012; IEA, 2009). In a review of E4 models, Schäfer (2012) concluded that accounting for behaviour changes in E4 models is "indispensable" when developing overarching climate change mitigation strategies for the transport sector.

Several researchers have attempted to integrate transport behavioural features in bottom-up (BU) optimization E4 models. For this class of models, Venturini et al. (n.d.) recognize two main approaches to incorporate behaviourally realistic modal shift. One consists in linking the BU E4 model with an external transport model that handles the behavioural features and determines modal shares (E3MLab, 2014; Waisman et al., 2013; Girod et al., 2012; Brand et al., 2012). The other approach endogenously assesses modal shift within an energy system model, by enlarging the traditional model structure to include transport-specific variables and transport infrastructure (Daly et al., 2014; Pye and Daly, 2015; Tattini et al., 2018a; Tattini et al., 2018b). For instance, studies have attempted to identify the limits for the travel time that users are willing to spend for commuting, as well as the budget they are willing to commit toward transportation: Travel-Time Budget (TTB) and Travel-Money Budget (TMB), respectively (Schäfer and Victor, 2000). Typically, people are willing to spend an average of 1.1 hour/day on commuting and devote only a small fraction of the households' total budget (approximately 3-5%, for households that do not own a personal car) towards transportation (Schäfer and Victor, 2000). When income increases, users shift to faster modes of transportation; wealthier societies have increased mobility levels (Schäfer and Victor, 2000).

Discrete choice model is used as a methodology to model modal shift in transportation providing the statistical background on how users select the mode for commuting. Modeling studies in the field of travel mode choices have used discrete choice models (Chikaraishi and Nakayama, 2016), multinomial logit regression (Arbués et al., 2016; Thrane, 2015), nested logit (Lu et al., 2015), generalized extra value, mixed logit and probit (Can, 2013; Eboli et al., 2016) based on the random utility maximization theory (McFadden, 1978). These approaches

have some limitations, such as: i) the strict model structure needs to be specified in advance; ii) they are unable to model non-linear systems; and iii) they consider only conditions that hold across an entire population of observations (Shukla et al., 2013 In: Maggi and Vallino, 2016). However, due to heterogeneity of consumers and complex decision-making process based on a large number of parameters, behavioural changes concerning mode of transport are subject to high degree of uncertainty. Therefore, discrete choice models are not sufficient to model the complex behaviour involved in modal choice decisions. Moreover, researchers are usually interested to investigate the impacts of transportation plans on the behaviour of individual households, persons or subgroups (Shirzadi-Babakan et al., 2015).

An alternative approach is agent-based modeling (ABM), which is capable of simulating a large number of heterogeneous individuals with different attributes, characteristics, behaviour and perception presented as agents. Agent-based modeling and simulation (ABMS) is an approach for modeling complex systems composed of interacting and autonomous agents (Macal and North, 2010). ABM is distinguishable from other approaches when it comes to the concept of agents represented as autonomous and interacting entities (Gilbert and Troitzsch, 1999). Indeed, ABMs are useful to analyze the non-linearity of aggregated behaviours with respect to individual ones (Maggi and Vallino, 2016). Ahanchian and Biona (2017) provided an extensive list of researches using ABM approach within different contexts.

During the past decade, several studies have used agent-based modeling approach within the context of traffic. Table 1 lists studies that use ABM as a tool for analysing transport. The review of the literature shows the importance of incorporating behavioural aspects in traffic related analysis and the capability of agent-based modeling approach to simulate people behaviour. However, the studies regarding mode choice consider only an urban area (city) as a geographical scope. Maggi and Vallino (2016) in their critical review of literature on ABM focusing on transport concluded that there is still a gap in urban transport AB modelling: They are usually focused on sub-categories of city inhabitants, such as school pupils, students, pedestrians or car owners, without a systemic view. Moreover, they discussed the need to implement real surveys in order to calibrate the ABMs using first-hand data (Maggi and Vallino 2016).

Table 1

Literature containing ABM as a tool for transport studies.

Reference	Geographic Scope	Focus	Input data
Dia, 2002	Brisbane, Australia	Modelling individual driver behaviour	Behavioural survey of drivers
Shafiei et al. 2012	Iceland	Predicting the evolution of market share of electric vehicles	CreditInfo report
Mallig et al. 2013	Stuttgart, Germany	Modeling travel demand	Travel survey and official statistics
Fagnant and Kockelman, 2014	A hypothetical mid-size city in US	Shared autonomous vehicles and environmental implications	US National Household Travel Survey
Novosel et al. 2015	Croatia	Simulate hourly distribution of transport demand	Official data of the region
Hager et al. 2015	Stuttgart, Germany	Modeling the traffic behavior in growing metropolitan areas	Household survey and statistics
Shirzadi-Babakan and Taleai, 2015	Tehran, Iran	Evaluate impacts of different transport development plans on choices of residential location and commuting mode of tenant households	Survey and official statistics
Zou et al. 2016	Beijing	Predict mode choice and departure time changes	Behaviour survey of travelers
Djavadian and Chow, 2017	Oakville, Ontario	Modeling 'Mobility as a Service' with a two-sided flexible transport market	Network data for Oakville and Transportation Tomorrow Survey

In our study, we develop a novel agent-based model, Agent-Based Modal Shift Simulation for Denmark (ABMoS-DK), and apply it to modal shift in the inland transportation sector in Denmark. The novelty of ABMoS-DK is that it 1) considers the full heterogeneity of travelers' rational decision-making using national travel survey data; 2) calculates the utility of different modes using both tangible and intangible costs; 3) chooses the fastest and cheapest mode to meet travel demand; 4) uses a bottom-up and non-linear approach to determine the potential for shifting away from private cars from the viewpoint of travelers in Denmark.

ABMoS-DK is used to address the following research questions:

1. How effective are strategies for influencing the travelers' decision on choosing the mode of transport?
2. How much is the maximum shift potential from the viewpoint of travelers without considering technological changes?
3. Which groups of agents (e.g., geographical zones, travel demand length, urbanization pattern and income group) are most sensitive to various strategies for incentivizing modal shift?

2. Data and Methods

2.1. Data

Based on the Great Belt Corridor, Denmark is divided to East (DKE) and West (DKW) regions. According to settlement patterns, each region is further divided into urban (U), suburban (S) and rural (R) areas (Eurostat, n.d.).

Figure 1 shows the structure for the data collection and how it relates to the calculations done in ABMoS-DK. The Danish National Travel Survey (also denominated TU survey), an interview-based survey that documented the travel behaviour of the Danish population by recollecting mobility diaries, and socio-economic data from 2006 to present were used to capture the characteristics of travelers (Christiansen and Skougaard, 2015). The socio-economic attributes on the household level (i.e., annual income, place of residence and car ownership) and the travel demand characteristics on individual level (i.e., trip length, departure time and trip purpose) were assigned to agents through an SQL database. The annual Danish population synthesis is taken from statistics Denmark (Statistics Denmark, n.d.) and is used to generate agents in future years out to the year 2050.

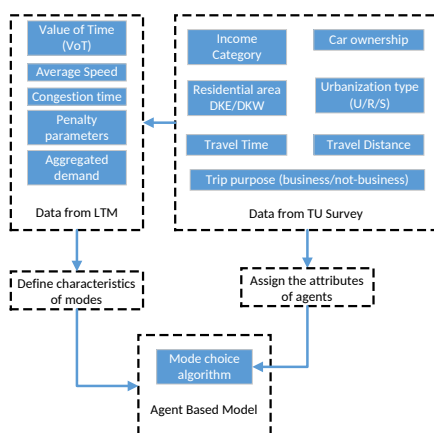


Figure 1. Data parameters within ABMoS-DK

The Danish Land Transport Model (LTM) was used (<http://www.landstrafikmodellen.dk>) (Rich and Hansen, 2015) as a supporting model of this study to determine the characteristics of different modes. LTM is a four-stage simulation transport model of Denmark (Rich, 2015),

which represents all transport activities within, into, and through Denmark (Jensen et al., 2017). LTM was used to quantify Value of Time (VoT), average speed of each mode across urbanization areas, average congestion time, penalty parameters of congestion, access/egress and waiting time together with the annual inland transport demand. Shares of transport modes in Bpkm are presented in Figure 2. The private cars are responsible for the majority of travel demand (84%), all public transits takes 12% and the train has the highest share (7%) followed by bus (3%), S-Train (2%) and metro (less than 1%) while the non-motorized modes take 4% of total inland travel demand.

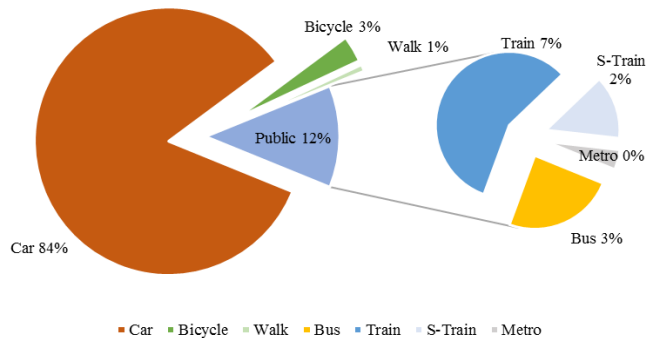


Figure 2. Shares of different transport modes in 2015, Million passenger kilometer (LTM)

Figure 3 presents the travel demand disaggregated on urbanization type in 2015 from LTM. It shows that most of the trips in DKE take place in urban area while in DKW, rural area has the highest share.

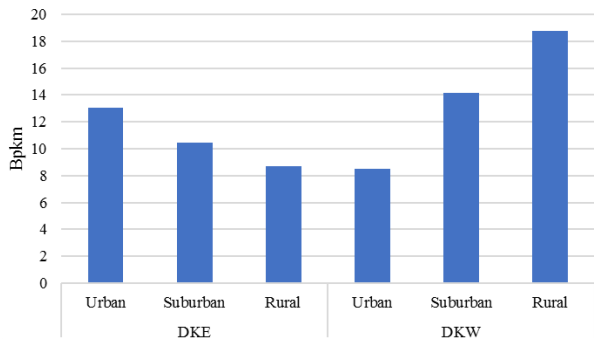


Figure 3. Travel demand disaggregated on urbanization type in 2015 (LTM)

2.2. Methodological framework

The methodological framework is presented in Figure 4. The base year of the model is 2010 and the model runs until 2050. First, the model reads the TU survey database and parametrizes the attributes of heterogeneous agents with socio-economic characteristics and travel demand from 2010 until 2015. Then each agent follows the mode choice algorithm. For modeled years after 2015 there are no data in the TU survey, so the model generates random agents using a Monte Carlo simulation. The generated agents follow the mode choice algorithm and ABMoS-DK exports the results.

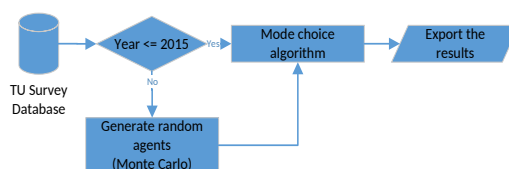


Figure 4. Methodological framework

In the TU survey, each interview has an associated a *weighting factor* that is determined in a way so that the surveyed population reproduces the real Danish population. In ABMoS, each agent represents a homogeneous consumer group with similar income level and place of residence. The weighting factor is used to specify the number of people represented by each heterogeneous agent. The consumers are grouped based on annual household income: Very Low (VL) less than 200 kDKK/year; Low (L) between 200 and 500; Medium (M) between 500 and 800; High (H) more than 800 kDKK/year. The classification of trip length is: Extra-short (XS) less than or equal to 5 km; Short (S) between 5 and 25 km; Medium (M) between 25 and 50 km; Long (L) more than 50 km. The place of residence is defined as DKE and DKW while the urbanization pattern is Urban (U); Suburban (S) and Rural (R). The agents look for an appropriate mode of transport in the traffic system to meet annual travel demand. They decide on the preferred mode of transport according to mode choice algorithm and personal characteristics.

The ABMoS-DK is capable of analyzing non-linear behavioural preferences of travelers and understand factors changing their rational behaviour towards shifting to more sustainable modes with bottom-up approach. The BU approach provides the opportunity to analyze the results on desired level of aggregation. This could help policy makers to analyze the potential of imposing policies in different geographical zones of region in question, specific group of

people (e.g., age, income, gender, education level, car ownership) and certain trip purposes in long-time horizon.

ABMoS-DK is simulated using AnyLogic multimethod simulation tool developed at Experimental Object Technologies (<http://www.xjtek.com>) which is a tool for modeling and simulation of complex systems (Borshchev et al., 2000; Borshchev et al., 2002). ABMoS-DK runs on any Java platform on the top of AnyLogic hybrid engine.

2.3. Modes of transport

Table 2 shows the availability of infrastructure, maximum constrained length and equations to calculate tangible and intangible costs of each mode of transport in ABMoS-DK, categorized as non-motorized, public, and private.

Table 2
The details of each mode.

	Availability of infrastructure	Maximum length (km)	Tangible Cost	Intangible Cost
Walk	All zones	15	N/A	Eq. (1)
Bike	All zones	25	Eq. (2)	Eq. (3)
Bus	All zones	Unlimited	Ticket price	Eq. (4)
Train	All zones	Unlimited	Ticket price	Eq. (4)
S-Train	Greater Copenhagen Area	63	Ticket price	Eq. (4)
Metro	Copenhagen City	14.2	Ticket price	Eq. (4)
Private car	All zones	Unlimited	Eq. (6)	Eq. (8)

2.3.1. Non-Motorized Transport (NMT)

The non-motorized modes of transport include walking and bicycling. There is no tangible cost associated with walking. However, walking and bicycling are options only available for extra short and short trips. As suggested by Hammadou and Papaix (2015), ageing largely influences walking activities. Therefore, if the agent is under the age 18 or over age 65, the average speed of walking across all urbanization types is decreased by 20%. The intangible cost of walking is calculated based on Eq. (1):

$$C_w^{Intangible} = VoT_{IC} \times (L_w^{Trip} / S_{w,UT,age}^{Average}) \quad (1)$$

where C stands for cost, w stands for walk, VoT is value of time changing across income class (IC), L stands for trip length and S is the average speed of walk changing across urbanization type (UT) and age. VoT depends on household income and changes across trip purpose (e.g.,

business vs. non-business trip) and expressed in the unit of DKK¹/min. VoT and average speed for each mode across urbanization type are taken from LTM.

Eq. (2) calculates the tangible cost of cycling. For electric bikes, on average, a 250-W battery will provide a range of 55 km, and the cost of charging is 5.25 DKK/kWh (Mobycon, 2014). Therefore, trips using electric bikes are constrained to 55 km and the tangible costs of cycling are given as:

$$C_b^{Tangible} = L_b^{Trip} \times (C_b^{Maintenance} + C_{if\ e-bike}^{Electricity} \times 0.024) \quad (2)$$

where, b denotes bicycle. The maintenance cost of cycling is taken from triangular probability distribution (i.e., min=0.01, max=1, mode=0.5) DKK/km. Cycling is only an option for agents younger than 75 years in ABMoS-DK. The intangible cost of cycling is calculated using Eq. (3).

$$C_b^{Intangible} = VoT_{IC} \times (L_b^{Trip} / S_{b,UT,age}^{Average}) \quad (3)$$

2.3.2. Public Transport

The public modes include bus, train, metro and S-train (urban-suburban railways). Tangible cost of each mode of public transports equals to ticket cost which are the function of length and calculated exogenously while the intangible cost of each public modes are calculated endogenously using Eq. (4):

$$C_{pu}^{Intangible} = VoT_{IC} \times (T_{pu}^{InVehicle} + (T_{pu,UT}^{Wait} \times Penalty_{pu}^{Wait}) + (T_{pu,UT}^{ACC/EGR} \times Penalty_{pu}^{ACC/EGR})) \quad (4)$$

where pu stands for public mode (i.e., bus, train, metro and S-train), T stands for time (minutes), $penalty$ parameters for waiting ($Wait$) time and access/egress time (ACC/EGR) is always constant and equal to 1.5, which are taken from LTM and represent the inconveniences associated with waiting and access egress. The in-vehicle time is calculated using Eq. (5).

$$T_{pu}^{InVehicle} = L_{pu}^{Trip} / S_{pu,UT}^{Average} \quad (5)$$

¹ 1 Euro equals 7.447 Danish Kroner (DKK) as of 09 January 2018.

2.3.3. Private Transport

The tangible cost associated with private cars includes tire, maintenance, insurance, ownership tax, parking cost, depreciation cost and other costs Eq. (6) and the annual fuel cost all taken from FDM (2017) Eq. (7):

$$C_m^{Tangible} = L_p^{Trip} \times (C_a^{Fuel} + C_a^{Tire} + C_a^{Maintenance} + C_a^{Insurance} + C_a^{Tax} + C_a^{Dep} + C_a^{Other}) / M_a \quad (6)$$

$$C_a^{Fuel} = M_{a,p} \times FP / FE_p \quad (7)$$

where C_a denotes annual fuel cost (DKK/year), a stands for annual, p denotes private mode of transport, M_a denotes annual mileage (km/year), FP denotes the fuel price (DKK/liter) and FE represents fuel economy (km/liter). Eq. (8) calculates the intangible cost of traveling by private car while Eq. (9) calculates the in-vehicle time of the trip:

$$C_p^{Intangible} = VoT_{IC} \times (T_p^{InVehicle} + T_{p,UT}^{Congestion} \times Penalty_{p,TP}^{Congestion}) \quad (8)$$

$$T_p^{InVehicle} = L_p^{Trip} / S_{p,UT}^{Average} \quad (9)$$

where congestion time varies across urbanization type while congestion penalty varies across trip purpose (TP) both taken from LTM. Eq. (10) calculates the total cost of each mode.

$$C_m^{Total} = C_m^{Tangible} + C_m^{Intangible} \quad (10)$$

2.4. Mode choice algorithm

Figure 5 presents the mode choice algorithm, which determines whether to use non-motorized, public or private transport based on the traveler's personal attributes, expectations and availability of infrastructure. Within ABMoS-DK, agents are independent- the chosen transport mode for a given agent does not depend on the outcome for other agents. The traveler's heterogeneity is incorporated to take into account that different groups of users have specific preferences that affect modal choice.

For each possible mode, the utility is calculated based on tangible and intangible costs for the same trip, and the algorithm chooses the mode with the lowest total cost. The utility of each mode also depends on the socio-economic and behavioural characteristics of the households (urbanization pattern, income level, value of time). For instance, the competition between faster and more expansive modes (e.g. car) with slower but cheaper modes (e.g. bus

or rail) is ensured by evaluating the utilities of each mode based on the income category and expectations of the traveler. The decision rules are formulated as follows:

Rule 1: The infrastructure for driving a private car is defined as having access to car at household level and having driving license for an ordinary passenger car (i.e., category B).

Rule 2: The passenger of private car is not required to have a driving license.

Rule 3: If the agent is a member of car sharing scheme, the cost is equal to the duration of trip multiplied by cost of car sharing per minute plus the intangible cost associated with driving. The algorithm uses the same tangible and intangible costs for passengers in a car sharing scheme.

Rule 4: In urban areas during rush hour, the speed of private cars decreases by 30% while the congestion time of private cars increases by 30% calculated from LTM.

Rule 5: Only the alternative modes that are available in the agent's region are considered (Table 1).

Rule 6: Agents between 14 and 50 years old that own a bicycle may ride for up to 25 km. Agents older than 50 years old will have 20% higher intangible cost associated with riding a bicycle.

Rule 7: If the agent owns an electric bike, the electricity price and maintenance cost will constitute the tangible cost.

Rule 8: It is assumed that the agent could study or work while commuting on public transport (intangible benefit). Therefore, for educated agents commuting further than 25 km, there is no in-vehicle time associated with the intangible cost.

Rule 9: The algorithm compares the total cost associated with each mode and chooses the cheapest mode of transport.

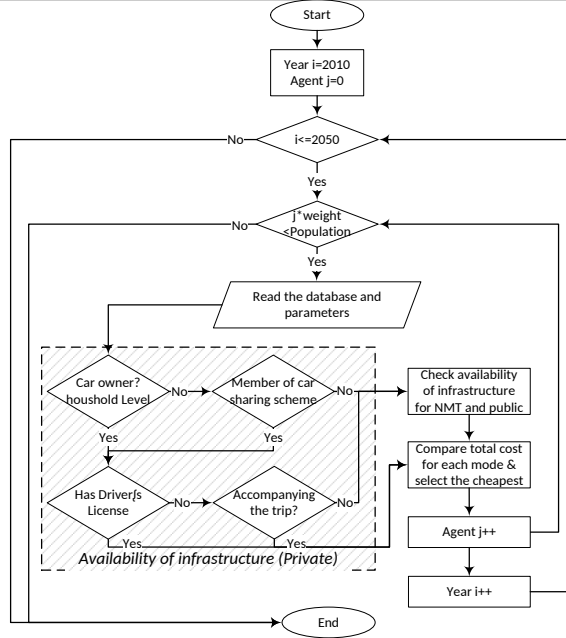


Figure 5. Mode choice algorithm in ABMoS-DK

2.5. Generating agents

The TU survey contains data for the model years 2010-2015. For the years 2016-2050, agents are randomly generated from the travel demand database and their associated characteristics are taken from the 2006-2015 data (TU). ABMoS-DK generates a random number $N \in [0, theLastIndexOfDatabase)$ and takes the attributes of N^{th} agent. This loop iterates until the stop criteria is satisfied. The stop criteria for generating agents is defined in Eqs. (11 and 12):

$$L_{UT}^{Trip} \times W^{Factor} \times N^{Days} \geq D_i^{UT} \quad (11)$$

where, L stands for trip length originated in one of the urbanization types (i.e., DKE/DKW, urban, suburban or rural), W is a weighting factor taken from TU survey representing the number of people with the same characteristics and travel demand in the entire Danish population. N is the number of days in a year (varies across working and non-working days). The right hand side of the Eq. (11) is the demand in year i taken from LTM disaggregated on

urbanization type. The sum of agent weighting factor is equivalent to population projections by statistics Denmark (P^i).

$$\sum_{year i} W^{Factor} \cong P^i \quad (12)$$

The criteria for generating agents are taken from the annual projection of demand by LTM disaggregated on the urbanization types and projection of population, which are fed into the model exogenously. In other words, the agents are generated using a Monte Carlo simulation such that the aggregation of demand in each urbanization area together with population synthesis matches the LTM demand and demographic data respectively.

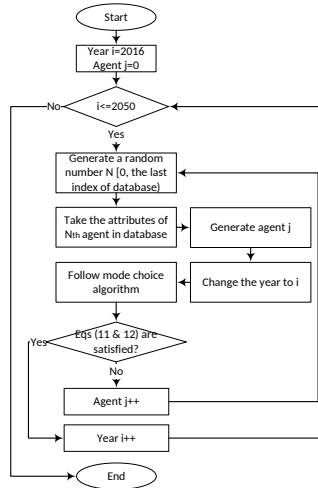


Figure 6. Generate random agents (Monte Carlo simulation)

Several trial runs were completed to determine how the number of Monte Carlo replications affected the confidence level. Figure 7 represents the Relative Standard Error (RSE) calculated using Eq. (13) for an increasing number of replications. Increasing the number of replications decreases the RSE while increasing the simulation time. The trial showed that 50 replications (generating approximately 11 million agents) results in a RSE well below 2% with a simulation time is 434 seconds (Figure 7).

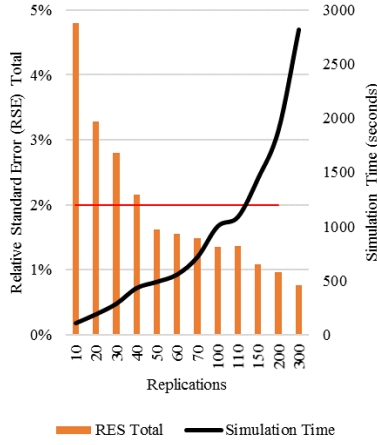


Figure 7. Required number of replications.

$$RSE_{Total} = \sqrt{\sum_{AllModes} \left(\frac{SE}{meanValue} \right)^2} \quad (13)$$

Fifty replications is in line with similar Monte Carlo-based studies of this nature. For instance, Qu and Zhou (2017) executed 10 iterations to reduce sampling errors. Boateng and Awuah-Offei (2017) run the Monte Carlo simulation 20 times with 20,000 agents. Ahanchian and Biona (2017) and Sopha et al. (2011) performed 30 replications.

2.6. Calibration and validation

ABMoS-DK is calibrated by adjusting the decision rules in the mode choice algorithm with the aim of reproducing the historical data of modal share in 2010 from LTM. The calibrated model is validated by reproducing the historical data of modal share in 2015 from LTM. The left hand side of Figure 8 shows the results of modal shares compared to the historical data from LTM in 2010 while the right hand side shows the results of modal shares compared to the historical data from LTM in 2015. The calibrated model is then run until the last year of simulation in order to forecast the modal shares.

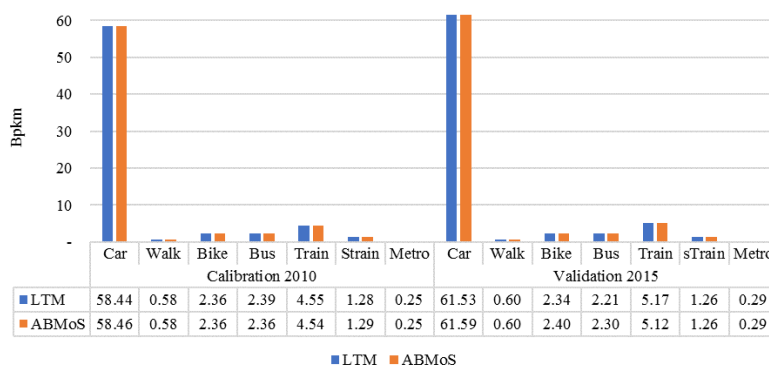


Figure 8. Calibration and validation

2.7. Scenario definition

One reference scenario and four alternative scenarios are developed and tested to determine the effect on modal shift, and shifts away from private cars in particular. All scenarios include the current expansion of existing Copenhagen Metro, which includes 15.5 km of new underground railway and 17 new stations. The new city ring line opens in 2020.

2.7.1. Business as Usual (BAU)

The BAU scenario represents a continuation of current conditions based on the TU and LTM. The BAU serves as the base (reference) scenario in our study.

2.7.2. Expansion of Infrastructure (EIN)

In EIN, we analyze the effect of developing metros in the DKW urban areas (i.e., Aarhus, Aalborg and Odense). S-Train railways would also be available in DKW urban and suburban areas by 2025, and the frequency of all trains and buses is increased by 10% with respect to BAU. Based on the timetable of public modes, some modes are not available in some areas during nighttime. In EIN, however, there is public transport available every two hours.

2.7.3. Incentives for Sustainable Modes (ISM)

ISM examines the impact of decreasing public transport ticket price by 20% in 2025. Additionally, free parking is available for Train and S-train, thus eliminating the access and egress time to public transport. The access and egress stage (parking a private car) is added to the primary mode of the trip. Finally, in ISM, all bicycles are electric with free recharging of the battery, thereby extending the maximum trip length to 55 km.

2.7.4. Disincentives for Private Cars (DPC)

DPC examines increasing the fuel tax by 50%; increasing registration and annual ownership tax of a fossil fuel dependent vehicle by 50%; doubling the parking cost, and collecting toll on vehicles coming into Copenhagen (30 DKK per trip irrespective of trip length during weekdays from 6 am to 6 pm).

2.7.5. Combination of all scenarios (COM)

Alternative scenarios act independent of other scenarios while integrating policy instruments to achieve greater performance from the overall strategy (May et al., 2006). In this policy, the combination of EIN, ISM, and DPC scenarios are integrated together.

3. Results

ABMoS-DK determines the maximum shift potential in the inland transport sector of Denmark from the perspective of consumers. The Monte Carlo simulation was performed 50 times and the results in this section present the mean value. Figure 9 shows the forecast of modal split (Billion-passenger-kilometer) for the inland modes aggregated on all geographical zones, all income categories and all trips. The trend shows that total demand is increasing by around 31% in 2050 compared to base year. The alternative scenarios show that modal shift takes place from 2030 onwards. In all scenarios, private car has the highest modal share, because of its availability almost everywhere, often associated with higher travel speed and in some cases, with lower total costs. Train ridership is in the second place due to relatively higher speed, comparative low cost for long trips and ability to accomplish long trips, while busses are more popular for short and medium trips.

In BAU scenario, all modes increase due to travel demand mainly dominated by private car. Although demand for Metro increases by more than 2.3 times in 2050 compared to base year, it still has the lowest share among the other modes. This is due to the fact that metro infrastructure is only available in the city of Copenhagen. Walking has almost the same share during the simulation period due to its high intangible cost. The results of EIN scenario shows that as expected, expansion of metro and S-train infrastructure provide opportunities to increase their ridership. Moreover, increasing the frequency of public transit decreases the waiting time thus, the intangible cost of public modes decrease. The trends show that there is shifting potential for Metro and S-train by more than 7 times and 2 times respectively in 2050 compared to BAU and reduce car use by around 5.4 Bpkm in 2050. The EIN scenario only

changes the parameters of public transit so they compete with private car. Therefore, other modes experience slight changes with respect to BAU.

The result of ISM scenario shows that incentivizing the public transit increases the share of public modes from 11.3 Bpkm (BAU) to 24.4 Bpkm in 2050. Increases in S-train, train and metro ridership are responsible for the majority of the increase in public shares while bus experiences a slight change relative to BAU. Bicycling also increases by around 66% compared to BAU while walking decreases (-29%) due to high intangible cost. The ISM scenario results in car use reduction by around 15.5 Bpkm in 2050. The results of DPC scenario show that the share of public modes increases from 11.3 Bpkm (BAU) to 30.0 Bpkm in 2050. Train, metro, bus and S-train ridership are responsible for the increase of public transit shares respectively. Bicycling also increases from 2.4 Bpkm to 6.6 Bpkm while there is only a slight change in walking. The DPC scenario results in car use reduction by around 23.1 Bpkm in 2050. Combination of all scenarios simultaneously increases the share of public modes from 11.3 Bpkm (BAU) to 38.7 Bpkm in 2050. S-train, train, metro and bus ridership are responsible for the increase of public shares respectively. Bicycling also increases from 2.4 Bpkm to 13.4 Bpkm and walking decreases by around 54%. The combination of all scenarios results in car use reduction by around 38.1 Bpkm in 2050.

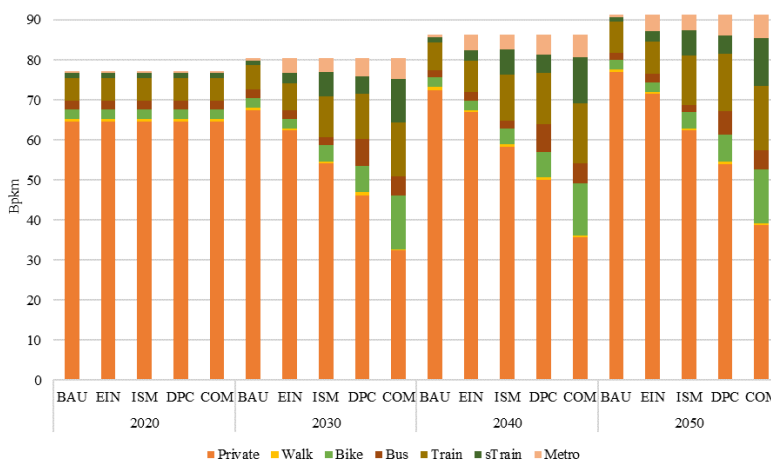


Figure 9. Maximum mode shift potential (billion passenger-kilometer)

Figure 10 shows the maximum modal shift potential in DKE and DKW in 2050 under each scenario. The total demand in DKE and DKW are 39.8 Bpkm and 51.6 Bpkm respectively and this does not change in either region under the different scenarios. Private cars have the highest share in both regions under BAU (i.e., 32.4 Bpkm in DKE and 44.6 Bpkm in DKW). However, the results show that implementing strategies in DKE is more effective at reducing car use compared to DKW. For instance, the strategies in EIN, ISM, DPC and COM reduce car use in DKE by 10%, 31%, 43% and 61% while in DKW they reduce car use by 5%, 10%, 20% and 41%, respectively. Train has almost the same share (8.4%) in both regions and the share could be increased to 15% and 19% in DKE and DKW respectively under COM. Under BAU, ISM and DPC, the S-train and metro infrastructure are not available in DKW. However, under EIN S-train and metro could accommodate 1.3 and 0.7 Bpkm respectively while under COM scenario these values could reach 3.1 and 0.8 Bpkm respectively. The share of bicycling in DKE is 2.9% while in DKW the share is 2.4%. Apparently, the strategies within EIN do not affect bicycling while the strategies in ISM increase the share of bicycling to 4.4% and 4.3% and DPC encourages travelers to use bike and increase the share of this mode to 6.8% and 7.4% in DKE and DKW respectively.

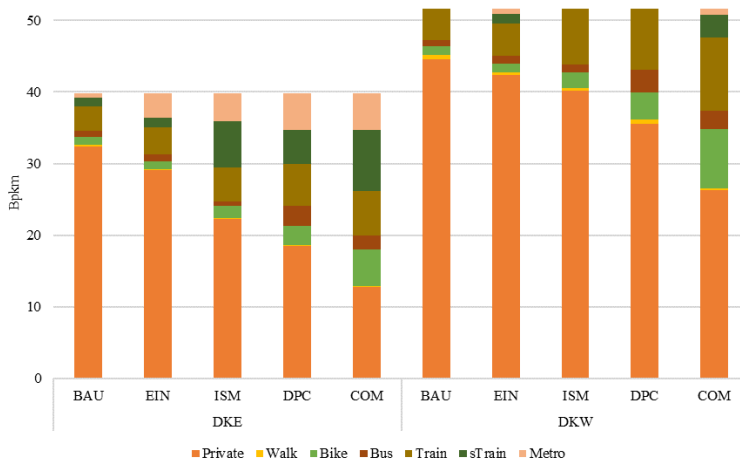


Figure 10: Modal shift potential in 2050 (DKE vs. DKW)

Figure 11 shows the maximum modal shift potential disaggregated based on trip length in 2050 under each scenario. The scenarios do not affect the total demand in each group of trip length. The long distance trips have the highest share of Bpkm (40%) followed by short

distance (30%), medium distance (20%) and X-short distance trips (10%). Under EIN, car use is reduced in short, long, medium and extra short trips by 9%, 8%, 5% and 2%, respectively, while under ISM car use is reduced in medium, long, short and extra short trips by 26%, 25%, 11% and 3%, respectively. The strategies within DPC reduce car use in long distance trips by 36%, medium (27%), extra short (27%), short (26%) and shift the users to public transits. In all scenarios, metro affects mainly short trips and has a slight contribution in medium trips (due to expansion of Copenhagen metro). Train is only a choice for medium and long trips while metro is not choice for long trips.

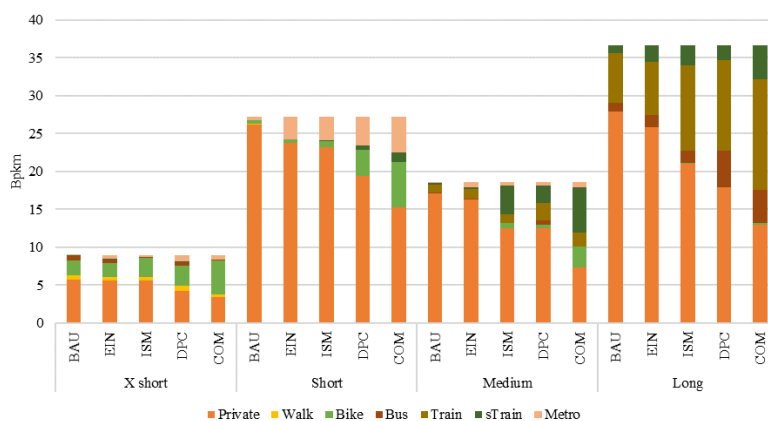


Figure 11: Modal shift potential in 2050 (trip length)

Figure 12 shows the modal shift potential in 2050 according to urbanization pattern. Metro is only a choice in Copenhagen area, while S-train is not available in rural areas. Therefore, private cars are responsible for the majority of trips in rural area. The results show that due to long distances, the majority of trips take place in rural areas. The policies analyzed are more effective in urban area: COM reduces car use in urban area by 71%, suburban area by 58% and rural area by 30% in 2050 compared to BAU. This is due to longer trips and limited availability of public transit in rural areas. In urban and suburban areas, the public transits play a significant role as substitute for car use while in rural areas, bicycling becomes an important mode of transport in lieu of cars.

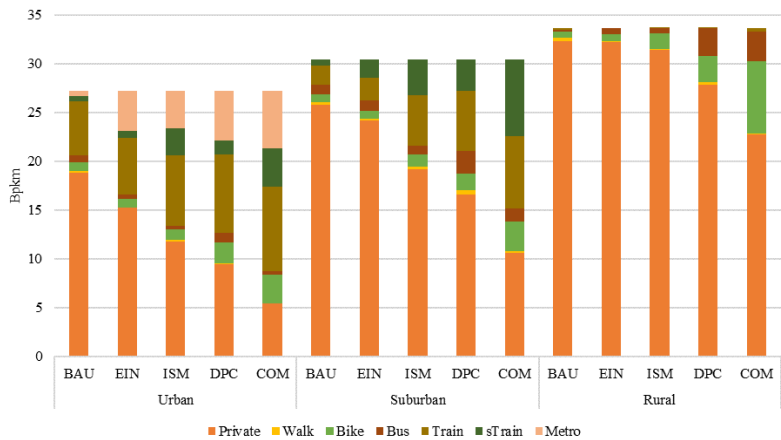


Figure 12: Modal shift potential in 2050 (urbanization pattern)

Figure 13 shows the modal shift potential in 2050 according to income groups. The strategies in the COM scenario are the most effective for the very-low income group: car use in the very low income group is reduced by 73%, low income group by 40%, high income group by 36% and medium income group by 30% in 2050 compared to BAU. Wealthier people prefer to spend less time in transport modes so they choose the faster but more expensive modes of transport. Moreover, the results show the lower the income, the higher the tendency to use non-motorized modes of transport. Bus has a 12% share under COM for very low income categories and the popularity of this mode decreases by increasing the income. Metro has almost the same share among the income categories while train and S-train are preferred by those in the medium and high income categories.

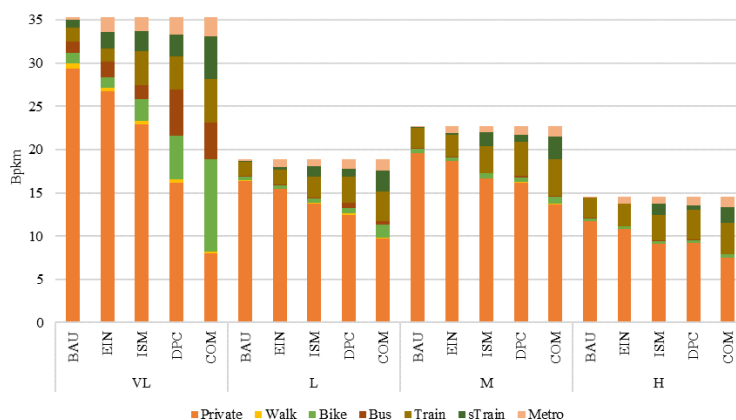


Figure 13: Modal shift potential in 2050 (income group)

4. Discussion

4.1. Methodology insights

The model framework adopted for this study has several advantages compared to other methods for evaluating modal shift potential. First, ABMoS-DK is capable of evaluating the effect on modal shift from a wide range of policies, e.g. involving the level of service of the modes, consumers' perceptions, support schemes to public transport and disincentives to the use of private car. Second, ABMoS-DK is flexible with regards to the level of aggregation. Third, ABMoS-DK is scalable, as it allows the evaluation of modal shares for a smaller portion of the entire system represented. Fourth, it is robust, as it provides consistent results that closely match those of the LTM. Finally, it is fast, taking approximately 15 minutes to assess modal shares for any scenario.

However, our approach also has some limitations. The level of service of the modes (e.g. car congestion time, car travel time, bus waiting time) do not depend on the size of the car stock nor on the amount of public transport vehicles available; these are not endogenous in ABMoS-DK. Moreover, the methodology requires extensive survey data to define the characteristics of consumers, which are input to the model as agents' attributes, which could be challenging to acquire in some countries. Fortunately, national travel survey are widely available and have been used in many studies: United States (Wang, 2015; Zolnik, 2018), United Kingdom (Jahanshahi et al., 2015), Belgium (Saadi et al., 2017), Sweden (Liu et al.,

2016), Ireland (Rabbitt and Ghosh, 2013) and Denmark (Christiansen and Skougaard, 2015).

The modal perception of the agents, which drives their modal choice, is represented in a simplified way with respect to the traditional utility functions (Train, 1986). The modal perceptions are represented in the model as tangible and intangible costs, which are calculated with data widely available (ticket price, fuel price, vehicle taxes, value of time, average speed of each mode, average congestion time, access/egress and waiting time). From an energy-environmental perspective, the model does not account energy consumption nor any kind of emission. From an economic perspective, the model does not track the investment costs of the transport technologies nor those of the transport infrastructure. However, these limitations do not affect the objective of this study.

Overall, the methodology adopted for this study allows for an analysis of how modal shift occurs as consequence of certain policies in a fast, reliable and scalable way, while the availability of the data required makes it replicable for any other geographical context. The energy-environmental-economic limitations identified can be addressed in future research by soft-linking the ABMoS-DK model with an E4 technology-rich energy optimization model, e.g. TIMES-DK (Balyk et al., n.d.). The soft-link with TIMES-DK could open a new prospect to better represent the implications of human behaviour on the transport sector, evaluating the influence of modal shift on the future development of the energy system and the contribution of modal shift to the decarbonization of the energy system.

4.2. Policy insights

The analyses carried out within this study are meant to suggest to Danish policy makers which policy levers should be implemented to encourage a shift from private car to less carbon-intensive modes, such as non-motorized and public transport. This study has analyzed the modal shift resulting from a range of policy measures affecting the level of service of the modes and consumers' perception in Denmark. Public transport and non-motorized modes compete with car in different trip distances: the study found that metro, bicycle and walk are valid substitutions to car in short distance, while train, S-train and bus in long distance. The analyses discovered that for Denmark the highest modal shift potential away from car lies in urban areas, where more modal alternatives are available. Moreover, very low and low income groups are more receptive of the policies analyzed in this study and are most willing to shift away from car.

We find that expanding the public transport infrastructure would reduce car use by approximately 7% in 2050 compared to BAU. However, this result is contingent on many factors beyond the scope of ABMoS-DK, and further techno-economic feasibility studies are needed to reduce uncertainty in this estimate. Incentivizing public transit enables reducing car use by 19% in 2050 compared to BAU. Changing the Danish vehicle registration tax increasing the total purchase price of private cars would disincentivize the adoption of private cars and, according to our analysis, could reduce car use by 30% in 2050 compared to BAU. However, such change requires several government consultations and involves several stakeholders. The extra revenue from a higher vehicle registration tax could fund the expansion of public transport infrastructure and the incentives to public transport, ultimately making the shift cost-neutral. The various strategies are “complementary” (May et al., 2006) when combined; meaning that their combined implementation shifts more demand from car than each policy alone. Under an ambitious policy package to move away from private cars, Denmark has the potential to nearly cut car use in half by 2050 compared to BAU.

5. Conclusions

ABM is capable of simulating the modal choice behaviour and perceptions of a large number of heterogeneous individuals with different characteristics. This study presents ABMoS-DK, a novel agent-based modeling approach that allows to evaluate the modal split for the inland passenger transportation sector in Denmark. The socio-economic characteristics of heterogeneous agents are taken from Danish national travel survey and the characteristics of modes are formulized to calculate tangible and intangible costs using LTM as a supporting model. The agents as rational decision-makers, choose the fastest and cheapest mode to meet travel demand and the model determines the maximum shift potential from the viewpoint of travelers. The model determines endogenously the modal shares from 2010 until 2050 by simulating level of service of modes and consumers' behaviour to understand current transport modal distributions, factors affecting the travel mode choice decisions, and network performance through a number of policy scenarios. The scenarios are defined by manipulating the variables affecting tangible and intangible costs.

The analysis of the trend of modal split of the alternative scenarios points out that introducing effective taxation schemes, parking pricing and toll collection; decreasing the public transit ticket price, park and ride facilities and charging infrastructure for electric bikes; increasing the frequency and expansion of public transit infrastructure are applicable

measures for encouraging travelers to shift away from car use. The results of the scenario analysis suggest that implementing analyzed scenarios in DKE are more effective to reduce car use compared to DKW. Moreover, the major potential to shift away car use is for long distance trips while the analyzed policies are more effective in urban areas where more modal alternatives are available. Finally, very low and low income groups are more receptive of the policies analyzed in this study and are more willing to shift away from car. This result suggests that policy makers shall first target the most sensitive consumer groups.

ABMoS can be used by policy makers to analyze the potential modal shift resulting from imposing policies in different geographical zones, targeting specific consumer groups (with similar characteristics concerning e.g., age, income, gender, education level, car ownership) and certain trip purposes in the long-term. The soft-link with TIMES-DK complements the model with information related to energy and CO₂ emissions from modal shift and the model could be improved for policymaking. By understanding consumer preferences and behaviour regarding mode choice, we contribute to producing a plan for decarbonizing the Danish transport sector to achieve the decarbonization target by 2050.

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Paper 6

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**THE COST OF ELECTRIFYING
PRIVATE TRANSPORT – EVIDENCE
FROM AN EMPIRICAL CONSUMER
CHOICE MODEL OF IRELAND AND
DENMARK**



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The cost of electrifying private transport – Evidence from an empirical consumer choice model of Ireland and Denmark

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ABSTRACT

There is a growing consensus that moving to a low carbon future within the transport sector will require a substantial shift away from fossil fuels toward more sustainable means of transport. A particular emphasis has been given to battery electric vehicles (BEV) and plug in hybrid electric vehicles (PHEV), with many nations investing in improving their charging infrastructure and incentivising electric vehicle purchasing through offering grant schemes and tax relief to consumers. Despite these incentives, the uptake of BEVs and PHEVs has been low, while some countries, such as Ireland and Denmark, are in the process of removing the tax relief currently in place. This initial retraction has already been met with a fall in sales of BEVs and PHEVs, which is expected to continue decreasing as these incentives are further reduced. This study develops a socio-economic consumer choice model of the private transport sector based off national empirical data for Ireland and Denmark to analyse the long-term effects of these subsidy retractions, and to further analyse the policy measures and associated cost of moving toward a low carbon private transport sector.

1. Introduction & motivation

There is a growing consensus that moving to a low carbon future within the transport sector will require a significant shift from its current state, whereby conventional fossil fuelled internal combustion engines (ICE) dominate the market, to sustainable means of transportation (IPCC, 2014). This shift is considerable, as it requires a fundamental change in both the fuel type and the vehicle technology of the transportation sector. Considering private transport, which constitutes 42% of global well-to-wheel (WTW) transport related emissions (IEA, 2017), this shift will involve multiple agents. *Fuel suppliers* may provide emission reductions through altering the composition of the fuels offered to consumers vis-à-vis the blending of bio-ethanol and bio-diesel with gasoline and diesel respectively or providing new fuels (e.g. CNG, LPG or H₂). *Automobile manufacturers* may provide efficiency improvements and innovative technologies capable of reducing downstream vehicle emissions. *Governing bodies* may impose regulations through fuel standards and minimal requirements for the performance of new vehicles while also incentivising the sale of low emitting vehicles. Finally, *consumers* – arguably the most vital agent in private transportation – choose which vehicle technology to purchase.

The potential emission reductions available from these former two supply agents are constrained by current technological

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limitations. European fuel standards, for example, mandate a maximum blend of conventional biofuel with petrol and diesel ICEs at 5% (CEN, 2008) and 7% (CEN, 2009) respectively, while the long-term efficiency improvement potential available to conventional ICEs has been identified as 28% and 33% for a spark ignition and compression ignition engine respectively, relative to a 2005 spark ignition engine (IEA, 2008).¹ While these measures offer potential short-term and medium-term solutions to meeting national emissions reduction targets, increasing the penetration of low-carbon alternative fuelled vehicles (AFV) will be imperative in advancing toward carbon reductions capable of adhering to a future with a global temperature rise limited to less than 2 °C (IEA, 2017). Despite this necessity, the uptake of non-ICE vehicles has been very low, suggesting that numerous barriers prevent a significant deployment of these vehicles. Moreover, the price of removing these barriers can be rather costly in the short-term, with little certainty surrounding effectiveness.

To quantify these barriers, the many costs pertaining to vehicle consumer choice can be loosely grouped as *tangible costs* and *intangible costs*. *Tangible costs* consist of the actual costs the consumer is faced with when choosing a vehicle, e.g., investment cost, operational and maintenance costs (O&M), taxation, and fuel costs. The nature of these costs allows for a quantifiable monetary figure to be associated with each factor. *Intangible costs*, however, represent the many non-monetary perceived costs the consumer faces when using a vehicle, e.g., inconvenience due to low vehicle range and limited refuelling infrastructure, to acceptance of new and uncertain technologies and to fewer options about the characteristics of the vehicle, e.g., number of doors, colours available, size, etc. These costs are generally difficult to quantify, as their perception changes for different consumer groups. Nonetheless, for regulators it is important to account for these intangible costs in their planning as to elaborate effective strategies to remove these barriers.

This study presents a methodology which monetises these intangible costs using empirical data from national sources to create a dynamic consumer choice model of the private car sector for Ireland and Denmark. This consumer choice model is linked to a sectoral simulation model of the private car sector (the CarSTOCK model) to indicate the cost and potential effectiveness of policy interventions in the form of WTW carbon dioxide (CO₂) emission savings. Ireland and Denmark have been chosen as a case study as both are in the process of removing subsidies for battery electric vehicles (BEV) and plug in hybrid electric vehicles (PHEV) by the turn of the decade (see Fig. 1 for a detailed breakdown) (Department of Finance, 2017; Skatteministeriet, 2015). In the case of Denmark, the initial retraction of the VRT subsidy for BEVs and PHEVs in 2016 was met with a drop in combined BEV and PHEV sales of 42% relative to the previous year (EEA, 2017). These subsidy withdrawals have been announced despite both countries identifying the necessity of electrifying transport in moving toward a low carbon future (DECLG, 2016; The Ministry of Climate Energy and Building, 2013).

The purpose of this study is threefold; (i) to contribute to the current body of scientific literature surrounding the area of modelling consumer choice within the private transport sector through use of qualitative data, (ii) to determine the effect of revoking tax relief for BEVs and PHEVs in Ireland and Denmark on stock and emissions, and (iii) to determine the cost and effectiveness of implementing further governmental level policy measures incentivising BEV and PHEV purchasing. In keeping with the order of these points of purpose, this paper is structured similarly. Section 2 discusses the value of modelling consumer choice within the transport sector, Section 3 describes the model inputs, structure and operability, Section 4 presents the impact of varying the market determinants mentioned above and Section 5 concludes.

2. The importance of modelling consumer choice

There is a growing body of literature which emphasises the necessity of moving away from models driven solely by economic parameters by including attributes related to consumer behaviour, thus enabling a more accurate representation of consumer choice (Byun et al., 2018; Garcia-Sierra et al., 2015; He et al., 2012; Mabit, 2014; Tattini et al., 2018; Zhang et al., 2016). This is imperative when analysing how to facilitate the shift toward sustainable mobility: without differentiating heterogeneous consumer groups and capturing the barriers that oppose the uptake of alternative fuelled vehicles (AFV) for these groups, both governing bodies and modellers alike are liable to an over-simplified representation of the market which they are attempting to alter. This over-simplified representation in turn may lead to unrealistic scenarios for the modeller and ineffective policies for the policy maker.

In an ideal consumer choice model, each agent would have a singular representation, with every applicable behavioural attribute accounted for to determine the utility of each vehicle available to purchase. In this way, the least-cost process of improving AFV utility for each consumer could be tackled. Of course, the scope of such an ideal representation would not only require a substantial level of computing power to model, but also an extensive data set to drive achievable, possibly through a comprehensive stated preference survey (SPS). There is a certain need for consumer specific data to accurately model vehicle consumer choice (Daziano and Chiew, 2012), although the availability of data is constrained. Thus, while aiming at developing a representative and valid model, we need to limit both the number of consumer segments and applicable behaviour attributes.

2.1. Consumer segments

Behaviour economics and psychology play a central role in breaking down the complex nature of the rationale behind consumer behaviour into comprehensible segments (Mattauch et al., 2016). These segments can be defined by many different attributes, e.g., demography, geography, and driving profiles. While consumers can be defined by a wide ranging array of these segments branches, it

¹ These efficiency improvements are gained through a combination of reducing engine friction, starter-alternator components, variable valve lift and timing, advanced cooling circuits, electric water pumps, and transmission improvements.

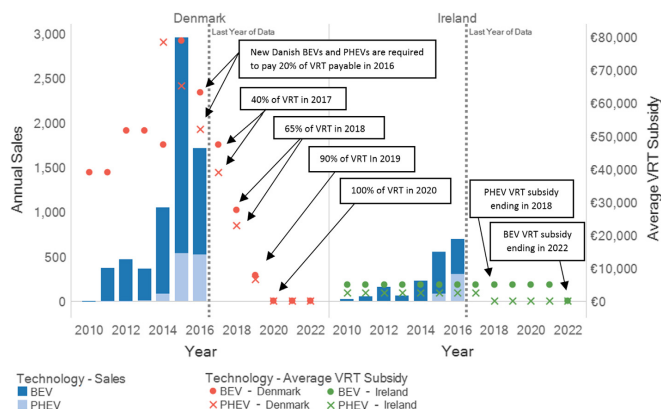


Fig. 1. Sales of BEVs and PHEVs in Denmark and Ireland (bars) and corresponding average VRT relief (the Danish VRT system is based on the cost of the vehicle (105% of the first 81,700 DKK (€10,800) and 180% of the remainder) with further slight subsidies for all vehicles dependant on fuel efficiency. The VRT relief for BEVs and PHEVs was calculated from the annual sales weighted average cost of the vehicle, while the projected VRT relief was calculated by holding the vehicle cost constant from 2015 onward and decreasing the VRT relief according to the text in Fig. 1) available (shapes).

is necessary to identify those which can be accurately represented (for the modeller) and those which can act as a policy lever (for the policy maker). Numerous studies have been dedicated to identifying these important behaviour attributes influencing consumer choice of private vehicles. For example, (Wilson et al., 2014) created a synthesis of 16 peer-reviewed articles which use discrete choice experiments informed by SPSS in examining preferences for AFDs. The studies analysed had a wide geographical range with findings that socio-demographic characteristics - particularly age, gender, and education - influence choices. Social influences were found to be important, although are rarely modelled. These characteristics can be used to segment consumers in adopter categories. Roger's classification of technology adopter types is a common framework for segmenting consumers, whereby the market is split into different classes of innovators (Rogers Everett, 1995). Combining the results of SPSS with Roger's diffusion of innovation theory provides a means of differentiating the innovators of a market, who would be the likely early investors in AFDs, from the laggards, who would be more reluctant from investing in new technologies. Creating these segments allows the modeller to vary behaviour attributes, e.g., range anxiety, for different portions of the market and for the policy maker to target consumer groups more effectively. Further examples of transport discrete choice models which segment the market by varying levels of innovations can be found in Brand et al. (2017), McCollum et al. (2016), and Bunch et al. (2015).

2.2. Behaviour attributes

As with consumer segments, the number of behaviour attributes which affect private vehicle-related purchasing decisions are wide ranging and are commonly left unrepresented in traditional energy system models. For energy systems models that wish to include heterogeneous decision agents, it is extremely difficult to represent all relevant behaviour attributes related to vehicle purchasing (McCollum et al., 2016), forcing these models to limit the inclusion of these attributes to those relevant for a specific research question.

This study draws upon the findings from the MA³T model, a nested multinomial logit (MNL) choice model developed by Oak Ridge National Laboratory, which uses the US National Household Travel Survey to determine the disutility costs (the non-monetary adverse effects faced by the consumer when purchasing a vehicle) associated with many of these attributes. Studies from this model determined vehicle model availability, risk related disutility, range anxiety, and refuelling/recharging infrastructure availability to be amongst the greatest contributors (Lin and Greene, 2011). This is broadly in agreement with the findings of both Wilson et al. (2014) and Sierczula et al. (2014), and thus stands as the extent of behaviour attributes examined within this study.

2.2.1. Model availability and risk related disutility

There are a wide range of vehicle characteristics which may influence a consumer's preference when purchasing a vehicle, e.g., car brand/model, vehicle cabin (sedan, hatch back, station wagon), engine type, car weight, car power, transmission system, number of doors, colour, alloy frame, etc. Although each of these characteristics can be individually classified as a behaviour attribute, they may be grouped under the overarching theme of model availability. Automobile manufacturers, in general, aim to provide a wide array of vehicles which fulfil the individual preferences of as many consumer segments as possible. Thus, the magnitude of the

disutility cost associated with model availability for a vehicle class rises as the number of models available fall, and vice versa.

Prior to achieving a substantial market share, new technologies are generally met with a varying level of aversion toward adoption, dependent on the consumer segment. The early adopters, in accordance with the theory pertaining to the diffusion of innovations, perceive this risk to be negative as the novelty of a new technology is appealing to this consumer group. On the other hand, their laggards' counterpart perceive it to be positive due to unfamiliarity. The disutility cost associated to this attribute is only relevant to AFVs as conventional ICEs are now widely accepted across all consumer segments. As the adoption of a particular AFV becomes widespread in a certain market, the risk related disutility converges on zero.

2.2.2. Range anxiety and refuelling infrastructure

There is a disutility cost associated with both range anxiety - a term used to encompass the perceived penalty associated with a failure to meet a daily travel demand due to limited battery range - and limited availability of refuelling infrastructure. Both of these disutility costs vary dependant on the travel profile of a consumer, while the magnitude of these costs varies based on the efficiency and range of a vehicle, alongside the recharging/refuelling infrastructure availability for the fuel used. Range anxiety has an associated penalty perceived by the consumer, which varies over time as a technology becomes more widespread. The disutility cost of range anxiety is faced only by BEVs, as the consumer acceptance of ICEs and PHEVs prevents any associated risk with this attribute. Refuelling infrastructure represents a disutility faced by all vehicle types, although the strong presence of petrol and diesel refuelling stations globally renders this cost to be minimal for ICEs.

3. Methodological approach

The approach employed by this study develops a non-linear consumer choice model of the private transport sector for Denmark and Ireland and links the outputs of this model to a sectoral simulation model of the private car sector to generate the resulting change stock and WTW CO₂ emissions due to governmental policies. Both models use the base year of 2015. This work has been largely inspired by previous discrete consumer choice models (Bunch et al., 2015; McCollum et al., 2016), and expands on these pieces of work through the integration of a sectoral simulation model and the reliance on publicly available data related to the private vehicle market.

The consumer choice model embodies the tangible costs faced by the consumer along with a monetised representation of the intangible costs related to model availability, risk related disutility, range anxiety, and refuelling infrastructure. These intangible costs are monetised via publicly available empirical data, where possible, to provide a method which is replicable for other countries with similar data availability. This study differs from most consumer choice models to date by relying on revealed preference of consumers shown through publicly available empirical data rather than stated preference, as was the case in Bunch et al. (2015) and Hackbarth and Madlener (2013).

This consumer choice model computes only the private vehicle market shares, and cannot determine the impact of policy measures on aggregate stock or emissions. To account for this, the CarSTOCK model is linked with the consumer choicemodel. The CarSTOCK model is a bottom-up techno-economic model which uses the market shares from the socio-economic consumer choice-model, in tandem with a technically detailed representation of the transport sector, to provide a full representative of the breakdown of stock, energy consumption, activity, and WTW CO₂ emissions in both Ireland and Denmark, thus determining the net effect of policy measures.

Scenario development is finally carried out within the consumer choicemodel, whereby policy specific scenarios pertaining to changes in vehicle registration tax (VRT), value added tax (VAT), annual motor tax (AMT), market regulation, and fuel costs, are created, resulting in detailed market shares of each 15 private vehicle technologies explored. These market shares are then entered into the CarSTOCK models for Ireland and Denmark to simulate the effect these policy measures would have on long-term stock, WTW CO₂ emissions, and energy consumption. This full method is summarised in Fig. 2.

3.1. Consumer choice model

The consumer choice model used in this study is a non-linear socio-economic Excel-based model built to estimate the effect of various policy measures on the private vehicle market. The market share (MS) for each vehicle is calculated based off the comparative perceived life cycle costs (LCC) of each vehicle technology using Eqs. (1) and (2), which are derived from the CIMS-US hybrid energy-economy model (Jaccard, 2009).

$$MS_{j,s} = \frac{(LCC_{j,s})^{-\alpha}}{\sum_{k=1}^K (LCC_{k,s})^{-\alpha}} \quad (1)$$

$$LCC_{j,s} = \left(CC_{j,s} * \frac{r}{1 + (1 + r)^{-n}} + MC_{j,s} + FC_{j,s} + IC_{j,s} \right) \quad (2)$$

In this approach, market share (MS) is calculated for each technology (j) and segment (s) in year n accounting for tangible costs - capital costs (CC) (which includes purchasing related taxes), maintenance costs (MC), and fuel costs (FC) - and intangible costs (IC) - which is a combination of costs associated with the behaviour attributes defined in Section 2.2. Capital costs are annualised, in order to be made comparable with all other costs, through the use of a discount factor r with a value of 25.7%, which is the current discount

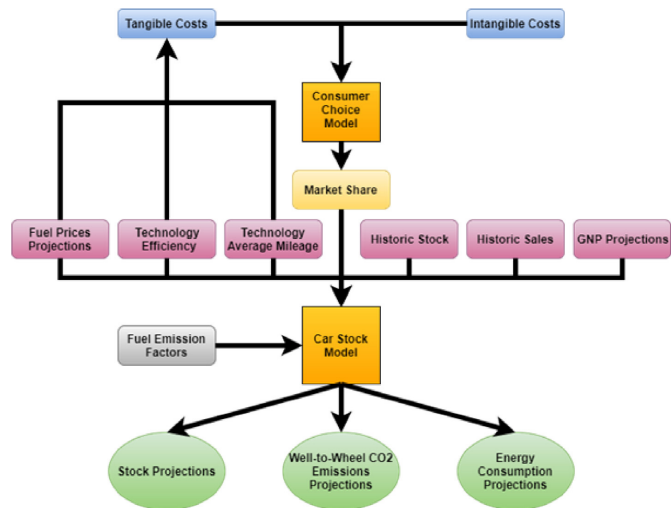


Fig. 2. Multi-model methodology.

rate for private cars adopted in the full CIMS-US model. This value was chosen for a discount factor as the methodology adopted by this study expands upon the original CIMS-US methodology, and so assumptions were aligned where possible. This falls within the range of vehicle related discount factors used from the review of similar values within literature carried out by Train (1985). A variance parameter (v_a) is introduced to enable a more behaviourally realistic allotment of market shares to the vehicle technologies. A high value of v represents a ‘winner takes all’ phenomenon whereby the lowest costing vehicle takes close to all of vehicle sales within a segment. On the contrary, a low value of v distributes sales more evenly regardless of differences in life-cycle costs, where a value of 0 produces a completely even share across all technologies. The variance parameter, v_a , was carried over from the CIMS-US model which uses a value of 15 (see Rivers and Jaccard (2005) for more details on the calculation of v_a). A sensitivity of the results through varying the variance parameter can be found in Appendix A. This study takes the approach adopted in CIMS-US further through consumer segmentation and substitution of the intangible costs with functions based on the model availability and range anxiety.

In both Ireland and Denmark this market is heterogeneous, so the segmentation of the market is critical to appropriate the variance in intangible costs accurately. Based on the review carried out in Section 2.1, the private vehicle consumer market is split into 18 segments divided geographically (urban/rural), by driving profile (Modest Driver, Average Driver, Frequent Driver) and by

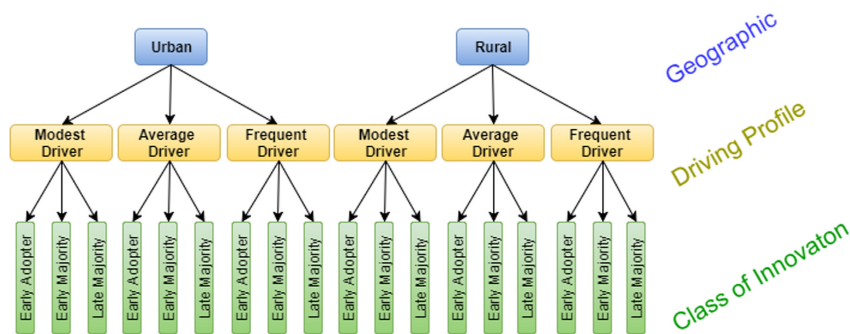


Fig. 3. Consumer choice model segmentation.

Table 1
Vehicle categories and classifications.^a

Vehicle classification	Ireland		Denmark	
	Engine size	Mileage (km/yr)	Engine size	Mileage (km/yr)
Small	< 1300 cc	14,102	< 1400 cc	14,257
Medium	1300–1700 cc	19,257	1400–2000 cc	18,263
Large	> 1700 cc	24,339	> 2000 cc	22,714

^a Data for Ireland for these classifications were collected from the National Car Test, which all private cars beyond four years old are obliged to take, and whereby the annual mileage of each tested vehicle is recorded. Data for Denmark has been obtained combining the inspection data of the Danish Road Directorate with the Administrative Car Register.

class of innovation (Early Adopter, Early Majority, Late Majority), as shown in Fig. 3.

The geographical split is made in accordance with the latest EU urban-rural typology (Eurostat, 2014). The driving profile segmentation is split by consumers with an average annual mileage of 15,000 km (modest driver), 20,000 km (average driver) and 25,000 km (frequent driver). A correlation between annual mileages and engine size (in cc's) was found in both Ireland and Denmark, whereby larger engine sizes were associated with larger annual mileages, while smaller engine sizes were associated with smaller annual mileages.² Therefore, technologies were categorised to correspond with these driving profiles (see Table 1) and the four ICE technologies considered (petrol, diesel, hybrid, PHEV) were split into 3 further bands: small (< 1300 cc), medium (1300 cc–1700 cc), and large (> 1700 cc), while BEVs were also split into 3 bands based off their range (< 125 km, 125–175 km, and > 175 km).

The classes of innovation are split by age groups, based on the synthesis of findings from the review of SPSs in Wilson et al. (2014) which found that: “Respondent age was consistently reported as significant in AFV choice with younger people more likely to choose different types of gas, electric, biofuel, and fuel cell vehicles”. The age groups were chosen from the census population data of number of people with eligibility to drive and split geographically into the groups of < 35 years (early adopter), 35–65 years (early majority) and > 65 years (late majority), as the share of these groups relative to the driving population were found to roughly correspond with the market share of Roger's innovation classes (Rogers Everett, 1995). It should be noted that other studies indicate that classes of innovators are represented by a wide-ranging set of characteristics. For example, Axsen et al. (2016) identify early adopters of plug-in electric vehicles in Canada as relatively higher income earners, which is understandable as in general plug-in electric vehicles are currently more expensive than their ICE counterpart. There are many other potentially determining factors such as environmental awareness, marital status, number of children, and type of employment. In an idealised study, each of these parameters would be used to classify the innovation propensity amongst consumers. However, this study relied purely on revealed preference data to calibrate the models used, and this level of information was not available for the geographical and driver profiling selected and hence the authors relied on the simplified assumption of associating age with class of innovator.

The remainder of this section discusses the sources of tangible costs, intangible costs, and provides a detailed modelling framework for the stock simulation model used.

3.1.1. Tangible costs

The total tangible costs – capital cost, operation and maintenance cost and fuel cost – were collected from a variety of publicly available national statistic sources for both countries. Historical data for each cost component were available for Ireland over the period 2004–2015 and in Denmark over the period from 1986 to 2015 for all data with the exception of purchasing cost, which was only available at a technology specific level until 2008 and so held constant until 2015. A summary of all cost components, corresponding value ranges, and sources are presented in Table 2, with a graphical summary of all tangible costs for the 15 technologies within the scope of this study shown in Fig. 4. A list of all data used to calibrate the model for the Irish and Danish models can be found in the Supplementary Information attachment to this article.

3.1.1.1. Projections of variables. Projections of vehicle capital costs are taken from Argonne National Lab's vehicle system simulation tool, Autonomie (Moawad et al., 2016), which has been used to compare a large number of powertrain configurations and component technologies. According to this model, the price of conventional ICEs are expected to increase due to measures required to improve vehicle fuel efficiency through light weighting, which is accompanied by an increase in the cost of materials such as aluminium or carbon fiber. An expected decrease in the cost of battery production and deployment results in a fall in the price of AFVs. A summary of these cost projections indexed against 2015 is shown in Fig. 5, and further insights into Autonomie's modelling framework can be found in Moawad et al. (2016).

The tax systems in place in the base year is held constant to 2050, although scenarios are later formed through the derogation of these taxes. Annual fuel costs are determined as a product function of annual mileage, technology efficiency, and pump fuel prices, with variances in the annual cost of fuel for each consumer segment expected as both technology efficiency and fuel prices change. Fuel price changes for both countries were based on projections of the increase in fossil fuel import prices from Capros et al. (2013),

² It should be noted that this assumption does not hold true for all consumers, i.e., some owners of a small sized engine car may drive much more than 15,000 km and owners of a large sized engine car may drive sparingly. However, the overall average trend of the available data indicated the adopted assumption stated here and was used as the best-found method of accounting for driving profiles through empirical data.

Table 2
List of tangible costs in Ireland and Denmark, 2015.

Tangible cost variable	Cost components	Ireland value range (2015€)	Ireland sources	Denmark value range (2015€)	Denmark sources
Capital cost	Purchasing cost excluding taxes	€11,512–50,054	SIMI (2017)	€7368–54,126	FDM (2017a)
	VRT	Based on CO ₂ emissions (14–36% of the open market selling price)	ACEA (2017)	105% of first €10,800 of the dealer's sales price and 180% [*] of the remainder, with reductions based on fuel economy and traffic safety equipment	ACEA (2016)
	VAT	23% of basic price of vehicle before VRT	Revenue (2015)	25% of the dutiable value at the time of their acquisition in new condition	ACEA (2017)
	Subsidy	€7500–10,000	Department of Finance (2017)	€59,003–90,785	Skatteministeriet (2015)
Operation and maintenance cost	Annual motor tax	Based on CO ₂ emissions (€120–2350/yr)	ACEA (2017)	Based on fuel economy (€34–4186/yr)	Skatteministeriet (2017)
	Insurance	€1003–1757	AA (2015)	€981–1295	FDM (201b)
	Fuel price	€1.53/ltr – Petrol €1.45/ltr – Diesel	AA (2017)	€1.50/ltr – Petrol €1.27/ltr – Diesel	Country Economy (2017)
	Fuel cost	€0.10/kWh – Electricity 6.66–0.91 L/100 km	Dineen et al. (2014)	€0.23/kWh – Electricity 8.48–0.91 L/100 km	FDM (2017a)

^{*} This value changed to 150% in 2016 (European Automobile Manufacturers Association, 2017).

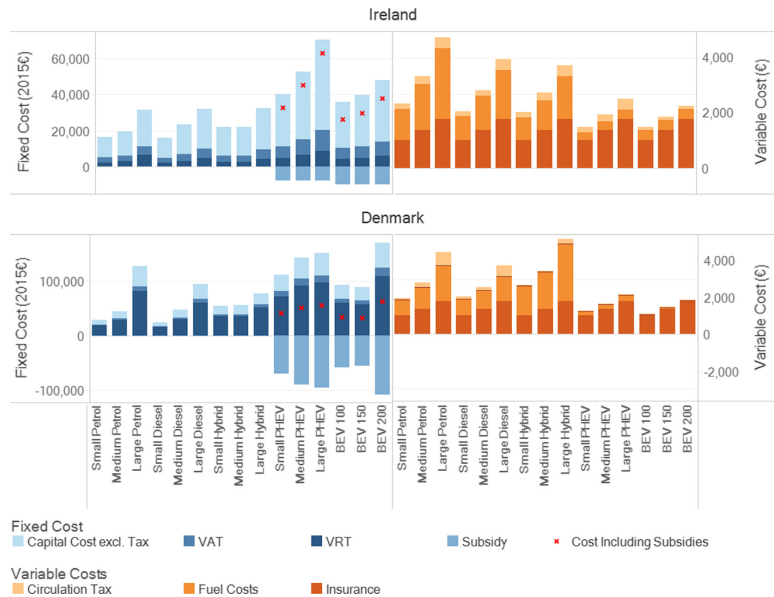


Fig. 4. Tangible costs in 2015 of all the 15 technologies included in the scope of analysis.

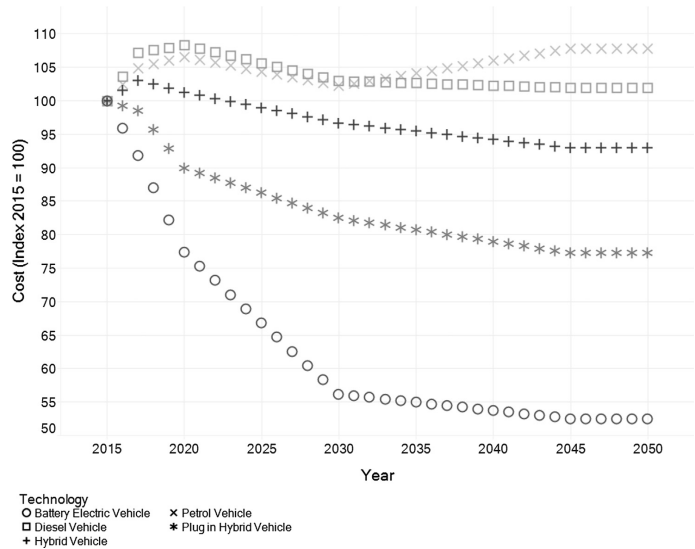


Fig. 5. Assumed projections of the tangible costs of the vehicle categories in 2015–2050.

while the improvements in vehicle energy efficiency were aligned with current European mandated manufacturer standards (European Parliament, 2009), and assuming maximum efficiency improvement by 2050 aligned with (IEA, 2008). Mileages were held constant from the base year.

3.1.2. Intangible costs

The role of intangible costs in these consumer choice models is to represent the non-monetary costs associated with vehicle purchasing as to draw a comparison between these intangible costs and the actual costs faced by consumers (tangible costs). Intangible costs have been introduced into consumer choice models as a means of providing more accurate competition between technologies in the past, e.g., (Bunch et al., 2015; Kamiya, 2015; McCollum et al., 2016). This subsection identifies the means through which this study monetises the main intangible.

3.1.2.1. Model availability/risk related disutility. Empirical data were used to determine the intangible costs associated with model availability and risk related disutility across all technology classes and consumer segments based off the number of models of vehicles available for sale. While no regional disparity is used for these costs, as it is assumed that the vehicle market is heterogeneous for both urban and rural areas, intangible costs are assumed to vary for consumers of varying driving profiles and adoption propensity. These intangible costs are applicable for all vehicles: a low representation of models available for a class of ICEs will pertain to a high intangible cost, as it would for AFVs. This approach allows the model to account for a potential fall in the availability of ICEs over time, which would then generate higher disutility costs for these technologies perceived by consumers. Vice versa, a rise in the number of AFVs available for sale would result in lower perceived disutility costs. The primary difference between ICEs and AFVs in this respect relates to the current standing of the market, which is currently dominated by diesel and petrol ICEs in both Ireland and Denmark, indicating that these vehicles are at the latter stage of the diffusion of innovation curve (low relative risk related disutility), while AFVs are at an early stage (high relative risk related disutility). This section first discusses the methodology adopted in line with this goal to introduce a model availability disutility cost for both ICEs and AFVs.

3.1.2.1.1. ICE model availability disutility. The competition between ICEs in a market independent of AFVs was initially analysed to determine the disutility cost associated with model availability for the late majority consumer segment – this study assumes that ICE vehicles are at the latter stage of Rogers' diffusion curve, and are thus assumed to represent the late majority consumer segment. The share of AFVs sold in both Ireland and Denmark over the period analysed was 0.08% and 0.19% respectively, and thus assumed to have had a negligible impact on consumer choice of ICEs. As first discussed in Section 3, different consumer driving profiles relate to different sizes of vehicles in both countries. Therefore, the intangible cost related to model availability for modest drivers, average drivers, and frequent drivers is determined by the available number of small sized cars, medium sized cars, and large sized cars respectively.

A non-linear intangible cost function depicting model availability was introduced and calibrated using the historic market share as a bench mark. The intangible cost relating to model availability varies by the number of models for each technology available, whereby a low number of a certain technology yields a high intangible cost, and vice versa (see Eq. (3)). Calibration of this function involved minimising the residual square error between the predicted and actual sales across each driving profile by varying the constants α and β for each driving profile (DP) within the Late Majority (LM) consumer segment. The values for these constants, along with the R^2 values when comparing the historic market share to that calculated by the consumer choice model after incorporating these generalised cost parameters is given in Table 3.

$$\text{Model Availability Intangible Cost}_{LM,DP} = \frac{\alpha_{DP}}{\beta_{DP} + \text{No. Models Available}_{DP}} \quad (3)$$

The number of models available for sale in Ireland between 2004 and 2015 of each technology is taken from the Society of the Irish Motor Industry (SIMI, 2017), as with the data for capital costs, while for Denmark a comprehensive list of models available from 1986 to 2008 is gathered from (FDM, 2017a). No comprehensive list of models available for sale was found for Denmark beyond 2008, so the number of different technology types sold (available from EEA, 2017) is used as an indicator for the rate of change in the model availability to 2015. The consumer choice model results with and without these cost curves are shown in Fig. 6.

It was deemed necessary to include these intangible costs as they enabled a stronger calibration of the model, shown in Fig. 6, and provided a high R^2 value across each driving profile.

3.1.2.1.2. AFV model availability and risk related disutility. The nature of a risk related disutility, which has been adopted by this

Table 3
Generalised cost curve parameters and corresponding R^2 for the frequent drivers consumer segment.

		Modest driver	Average driver	Frequent driver
Ireland	α	1.86E+05	2.16E+05	1.60E+06
	β	27.27	0.00	0.00
	R^2	0.998	0.899	0.832
Denmark	α	1.39+E06	1.51+E06	1.13+07
	β	192.87	119.75	439.67
	R^2	0.986	0.986	0.788

All values in bold have a significance level of < 0.001 .

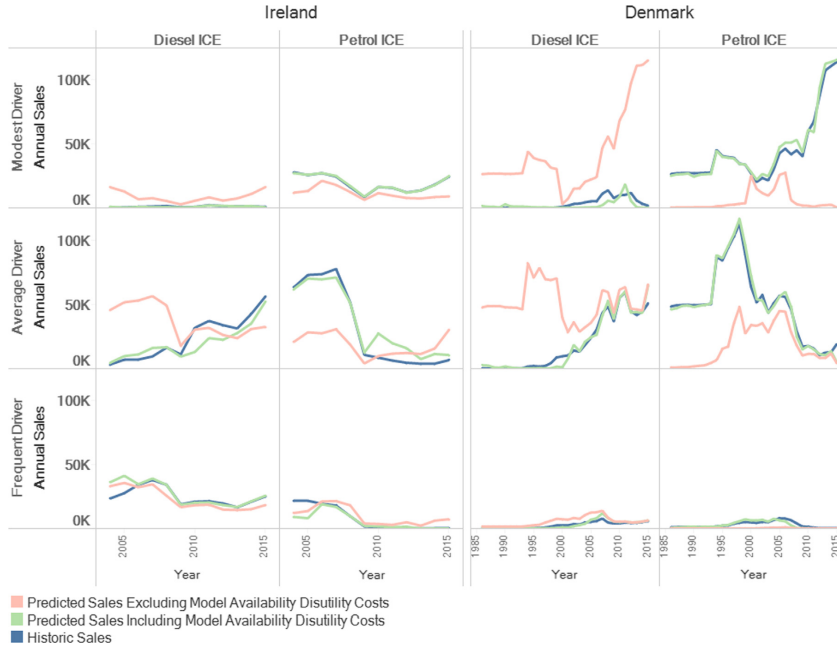


Fig. 6. Consumer choice model results for ICE vehicles, with and without model availability disutility costs.

study, accounts for the varying level of perceived risk within each consumer segment - early adopters associate a lower risk with the purchase of an AFV relative to that associated by the late majority. In an attempt to monetise this risk using quantitative data, this study created a non-linear regression model to analyse the variance in intangible costs of AFVs with respect to the number of models available for sale across the EU-28 using the publicly available database from the Environmental Energy Agency (EEA) on vehicle sales from 2010 to 2015. Vehicle sales figures from these databases were extracted and used as an input for a European consumer choice model (using Eq. (2)), with the same structure as that of the Irish and Danish consumer choice models, to determine the intangible costs for consumers of AFVs within each of the 28 EU member states. Technologies were segmented to align with those used in the Irish and Danish consumer choice model, and tangible costs were calculated using the vehicle cost excluding taxes from the Irish and Danish databases, with the varying level of tax rates for each member state calculated according to ACEA (2015). The generalised intangible costs for AFVs were then generated to align with market shares in each country in each year from 2010 to 2015. While the purpose of these databases was to show compliance with European emission standards, this study found a large number of discrepancies with the reporting of fuel types within the database. For example, in 2015 12,000 Citroen ICEs were wrongly reported as either 'petrol and electric' or 'diesel and electric' and subsequently published as PHEVs by the EEA. Furthermore, a large number of hybrids have been reported by the EEA as PHEVs. In 2015, the EEA reported 126,000 PHEVs sold in Europe, although after manually correcting misreported fuel types within these EEA databases, the actual sale of PHEVs in 2015 was found to be 82,412. In the 2016 release of this database, no further discrepancies were found.

Finally, a non-linear regression analysis was carried out using these intangible costs as dependent variables and using the number of AFVs available for sale within each country, extracted from EEA (2017) as explanatory variables. Eq. (4) was used to calculate the intangible cost pertaining to model availability for the early adopter (EA) consumer segment for different vehicles (ve). The parameters of this equation were generated from the regression discussed above, as it makes the assumption that all consumers of AFVs so far fall within the early adopter segment. To generate the parameters for the early majority segment, interpolation was carried out between the early adopter and late majority generalised cost curves. These factors are presented in Table 4.

$$\text{Model Availability Intangible Cost}_{EA,v} = \frac{1}{C_{0,ve} + C_{1,ve} * \text{No. Models Available}_{ve}} \quad (4)$$

Table 4
Generalised cost curve parameters for the early adopter and early majority consumer segments.

Technology	Constant	Early Adopter	Early Majority (Interpolated)
BEV_100	C ₀	7.70E–04***	3.85E–04
	C ₁	5.49E–05	2.98E–05
BEV_150	C ₀	4.27E–04**	2.14E–04
	C ₁	3.19E–05**	1.83E–05
BEV_200	C ₀	8.52E–05**	4.26E–05
	C ₁	8.88E–06**	6.75E–06
PHEV small	C ₀	1.10E–04	5.50E–05
	C ₁	3.38E–05**	1.98E–05
PHEV medium	C ₀	6.11E–05	3.05E–05
	C ₁	1.96E–05**	1.21E–05
PHEV large	C ₀	1.22E–05	6.09E–06
	C ₁	5.46E–06***	4.48E–06

*** Statistical significance at the $p < 0.001$ level.

3.1.2.2. Range anxiety/refuelling infrastructure. Range anxiety is defined in this study as the perceived disutility faced by a consumer in failing to meet a desired travel demand due to shortages in battery charge availability. As a form of proxy, this study first attempts to consider the variation in intangible costs for all 28 EU member states compared against the variation in charging point availability, with the logic that range anxiety falls as the number of charging points rise. A regression was established to consider this variation using the intangible costs (determined in Section 3.2 above) and the number of public charging points available from ACEA (2017). This regression, however, was found to have a low level of significance, concluding that there was an insufficient level of information relating to private charging points (such as work and home charge points).

Therefore, this study employs a similar approach as used by McCollum et al. (2016), whereby the daily travel profiles of each consumer segment are calculated using the gamma distribution curves generated by the MA³T model, and the failure to meet the daily travel demand on one day ensues a penalty. The penalty used to encompass both range anxiety and refuelling infrastructure is chosen by calibrating the model results to national sales in 2015 and decreases linearly to the cost of renting a vehicle (€117.89 for Ireland and €186.04 for Denmark³). The probability of BEV drivers meeting their daily travel demand is based on the number of charge points available (either a type 2 home charger, a type 2 work charger, or both) and the time spent charging (8 h at home, 7 at work). All BEV drivers are assumed to have access to at least one private charging point, and introducing a second charging point reduced range anxiety.

3.2. CarSTOCK model

The market shares are an output from the consumer choice model into a technology-rich private car sectoral simulation model to calculate the final stock, energy consumption, and emissions for both Ireland and Denmark. The original CarSTOCK Model (see Daly and Ó Gallachóir, 2011b) relied on assumed market shares of each technology while this paper expands on this approach by creating a hard-link between the consumer choice model and the CarSTOCK model. This link enters the calculated market shares for each of the 15 technologies into the CarSTOCK model which then executes calculations on stock, energy, activity, and emissions.

The Irish and Danish CarSTOCK models draw upon detailed national data statistics relating to the composition of the market, sales, average mileage, efficiency, and life-time of vehicles with a disaggregation of vintage, fuel type and engine size to produce a long-term evolution of the private car stock, energy use and related CO₂ emissions to 2050 based off the ASIF methodology developed by Schipper et al. (2000) which can be summarised by Eq. (6). In brief, total private transport related CO₂ is calculated as a sum of the product of vehicle activity (A), private car stock (S), energy intensity (I), and emission factors (F) for fuel type (f) and vintage (v). Projections of total activity and total stock are calculated endogenously within the CarSTOCK model, using gross national product (GNP) and fuel prices, linked with literature based elasticities of demand, as drivers.

$$\text{Transport Related CO}_2 = \sum_{f,v,t} A_{f,v,t} * S_{f,v,t} * I_{f,v,t} * F_t \quad (5)$$

Aggregate emissions for the private transport sector is calculated in this manner for each of the 15 technologies analysed. This model uses the structure of the Irish CarSTOCK model, which was originally developed for policy analysis in the area of private transport (Daly and Ó Gallachóir, 2011b) and has been updated using recent national data on an annual basis. This structure is replicated for Denmark using detailed national statistical data.

Activity is recorded in an annual vehicle inspection for both countries, whereby the annual mileage of each vehicle in the country is recorded. This data was accessed through the Sustainable Energy Authority of Ireland (SEAI) who processed this raw data into technology specific data, and from accurate odometer readings from the Ministry of Transport (MOT) tests for Denmark.

Stock data in Ireland is obtained from the Vehicle Registration Unit, who provides a detailed list of vehicles, accounting for fuel

³ Prices for Denmark and Ireland were based off 54 and 85 quotes respectively from 5 different car rental companies.

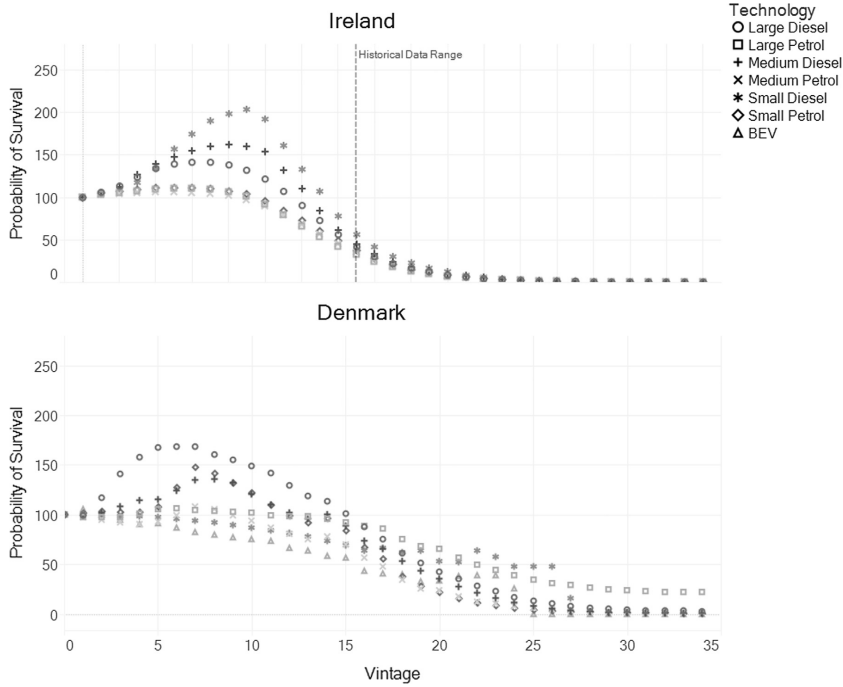


Fig. 7. Irish and Danish technology survival profiles.

type, engine size (ES) and vehicle vintage (vi). This data for Denmark is obtained combining the inspection data of the Danish Road Directorate with the Administrative Car Register. As this paper has previously shown that diverse technologies have different driving profiles (see Section 3, Table 1), it can be assumed that there is a variation in the level of deterioration for each technology. For this reason, a survival profile is built to account for an accurate lifetime of each vehicle type using this information in tandem with Eq. (5). The resulting probability of survival is presented in Fig. 7.

$$Survival\ Rate_{vi}^{ES} = Average \left(\frac{(Stock_{vi}^{ES} - Stock_{vi-1}^{ES})}{Stock_{vi}^{ES}} \right) * (1 + Survival\ Rate_{vi-1}^{ES}) \quad (6)$$

The oldest data available for Ireland was from the year 2000, resulting in survival profiles up to the age of 16 years being built. Data beyond this was extrapolated using an exponential decay in line with historic data. Data for Denmark was available since 1985.

Specific energy consumption of the historic fleet in Ireland disaggregated by engine band are obtained from the SEAI, who links national sales data of each vehicle to the manufacturer's specified energy consumption per km. Efficiency data for Denmark has been obtained combining the inspection data of the Danish Road Directorate with the Administrative Car Register. A comparison of the specific energy consumption of each vehicle type is shown in Table 5.

The fuel emission factors for petrol and diesel were taken from Dineen et al. (2014). Relating to electricity emissions, both Ireland and Denmark have made recent strides towards a low carbon power sector, aiming for 40% and 50% renewable electricity by 2020 respectively (DCCA, 2010), (Danish Energy Agency, 2015). Projections of electricity specific CO₂ emissions were taken from the EU PRIMES reference scenario, which assumes an emissions intensity in 2050 of 0.03 tCO₂/MWh in Denmark (down from 0.17 tCO₂/MWh in 2015) and 0.13 tCO₂/MWh in Ireland (down from 0.41 tCO₂/MWh in 2015) (European Parliament, 2016).

The drivers of the stock model, namely fuel price and GNP, are chosen following the methodology carried out in the original development of the Irish CarSTOCK model (Daly and Ó Gallachóir, 2011a) and replicated for Denmark. Projections of GNP are generated using the Economic and Social Research Institute long-term macro-economic model HERMES results from the Medium term review, 2013 (Bergin et al., 2013) and taken from OECD national projections for Danish projections. These projections are then linked with income and fuel elasticities of demand derived from Johansson and Schipper (1997) to generate projections of stock and

Table 5
Specific energy consumption by class of car technology for Ireland and Denmark in 2015.

Specific energy consumption (MJ/km)	Ireland	Denmark
Small petrol	1.83	1.45
Medium petrol	2.22	1.77
Large petrol	2.70	2.73
small diesel	1.60	1.15
Medium diesel	1.62	1.25
Large diesel	2.19	1.82
Small hybrid	1.38	1.38
Medium hybrid	1.37	1.37
Large hybrid	1.89	1.89
Small plug in hybrid	0.68	0.29
Medium plug in hybrid	0.68	0.69
Large plug in hybrid	0.77	1.00
Battery electric vehicle	0.64	0.62

activity (see Table 6).

4. Results and discussion

The consumer choice model produced satisfactory results of vehicle market shares for both the base year (2015) and first year of available data in both Ireland and Denmark (2004 and 1986 respectively). The resulting market share for both Ireland and Denmark in 2015, with and without intangible costs, are shown in Fig. 8. The results highlight the importance of accounting for the non-monetary parameters in order to have a reliable model.

In keeping with the original aim of this study - which sets out to determine the effect of revoking tax relief for BEVs and PHEVs, and to determine the cost and effectiveness of implementing further governmental level policy measures incentivising BEV and PHEV purchasing - the scenarios are set in a similar fashion. Firstly, a Business as Usual scenario (BaU) identifies the change in stock, emissions, and energy consumption from the base year to 2050 following a retraction of BEV and PHEV subsidies in line with currently national government policies in Ireland and Denmark. This scenario is developed upon whereby the impact of reducing the model availability of BEVs and PHEVs through increasing the number of models available for sale is explored. Secondly, multiple scenarios identifying the impact of government intervention, in tandem with external factors (i.e., beyond the control of national governance) are explored. These policy-induced interventions range from the reintroduction of a VRT subsidy for BEVs and PHEVs, introduction of a derogation of VAT for BEV and PHEVs, offering free electricity for vehicle charging, a derogation of the annual motor tax (AMT) for BEVs and PHEVs, and a regulation of the sales of ICEs. The external factors explored detail the varying level of BEV and PHEV vis-à-vis varying the number of models available – as neither Ireland nor Denmark produce automobiles, they must rely on foreign manufacturers to produce more BEV or PHEV models to reduce the model availability intangible cost. Finally, the cost and corresponding market uptake associated with the introduction of these monetary controlled incentives are presented.

The remainder of this section summarises the market shares calculated by the consumer choice model and the resulting final stock and emissions figures under these scenarios. These results represent the combination of the 18 consumer segments, but are the representation of the entire national market. Fig. 9 presents the various costs within the consumer choice model for one specific consumer segment - the urban, modest driver, early adopter segment for Ireland under a BaU. In this sample scenario, the capital costs for ICEs increase and the capital cost for BEVs and PHEVs decrease, while the model availability intangible costs for BEVs and PHEVs reduce due to a linear increase in the number of models available for sale. These changes in costs increase vehicles competitiveness within the model and increase the market share for AFVs. Each segment is calculated individually and later combined to give a comprehensive representation of the national car stock market.

4.1. VRT subsidy removal – BaU

4.1.1. Ireland

Under a BaU with no variation in the number of models available for sale, the market share of BEVs in Ireland rises from 0.39% in the base year to 1.2% in 2021, then falling to 0.3% once the VRT subsidy is removed in 2022. This market share then rises steadily to 4.5% by 2050, driven by the assumed reductions in the cost of BEVs and cost increases in ICEs (Moawad et al., 2016). The market share of PHEVs largely goes unchanged. The market share in the base year stands at 0.002% of all vehicles bought, and following the

Table 6
Fuel price and income elasticities of demand.

Elasticities of demand	Stock	Vehicle kilometres
Fuel price elasticity	−0.1	−0.1
Income elasticity	0.35	0.6

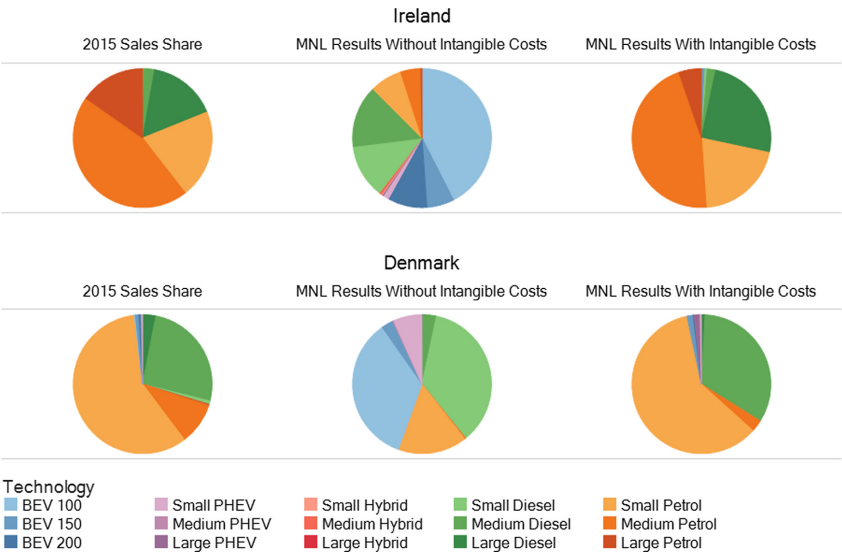


Fig. 8. Historic and model market shares for Ireland and Denmark for 2015.

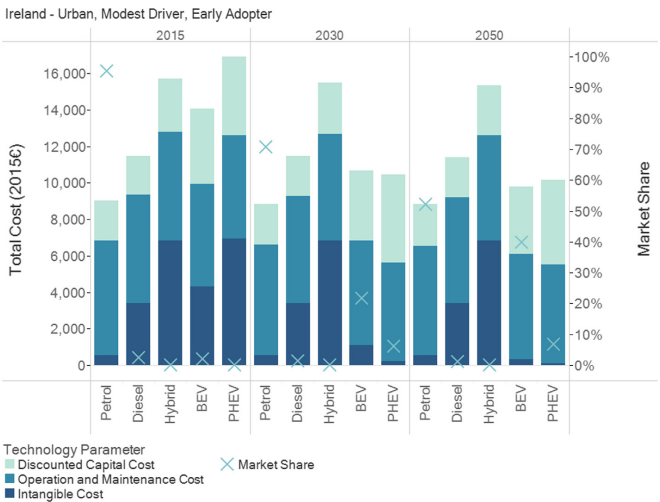


Fig. 9. Market share and associated costs for BaU with an increase in BEV/PHEV models available.

removal of the VRT subsidy in 2019, this is reduced to 0.001%. Despite reductions in the cost of this technology, there is no change in the market share by 2050 due to the low level of PHEV models available. Total AFV stock reaches 91,000 vehicles by 2050, with 3.46 million ICEs.

Emission reductions are still evident despite the low uptake of AFVs driven by ICE efficiency improvements. These efficiency improvements are in line with current European standards of manufacturer's achieving a maximum of 95gCO₂/km per vehicle produced by 2021 (European Parliament, 2009) and a regulatory proposal of setting this standard to between 68 and 78 gCO₂/km for 2025 (Mock, 2013). Efficiency improvements beyond this are assumed at a year-on-year value of 0.75%, in line with the total long-range potential efficiency improvements of ICEs by 2050 according to IEA (2008). These efficiency improvements coupled with the marginal electrification of transport provide a 19% reduction in well-to-wheel CO₂ emissions by 2050 relative to 2015.

4.1.1.1. Sensitivity due to model availability. A linear increase in the model availability of BEVs and PHEVs from their current standing to match the number ICE models currently available reduces the intangible costs for these technologies significantly and by 2050 increases their combined market share to 49%. This corresponds to approximately 1.4 million BEVs and 75,000 PHEVs in the private vehicle stock by 2050, and a 44% reduction in well-to-wheel CO₂ emissions relative to 2015.

4.1.2. Denmark

The initial retraction of the VRT subsidy in 2016, whereby BEV/PHEV consumers must pay 20% of the tax payable, sees a sharp fall in total market share of these vehicles, from a combined 3.2% in 2015 to 0.7% in 2020 when the subsidy is completely removed. The assumed improved efficiency within ICE vehicles increases competitiveness due to lower fuel costs, which in tandem with the assumed changes in the technology costs contributes to a marginal increase in market share of BEVs and PHEVs to a combined value of 1.7% in 2050. Total AFV stock reaches approximately 50,108 vehicles in 2050, while ICEs retain the lion's share at 3.64 million vehicles. Similar to the Irish results, this AFV penetration combined with the assumed efficiency improvements in ICEs generates an 18% reduction in well-to-wheel CO₂ emissions by 2050 relative to 2015, despite a 54% increase in total national vehicle stock over the same time period.

4.1.2.1. Sensitivity due to model availability. Increasing the number of AFV models available for sale to match that of ICEs in 2015 by 2050 results in a low increase in the market share of both BEVs and PHEVs, rising to 2.7% in 2050. This corresponds to a stock of 88,574 AFVs in 2050, and a reduction in well-to-wheel CO₂ emissions of 19% by 2050 relative to 2015. The uptake of AFVs is significantly lower than that of Ireland due to the significant rise in costs of EVs and PHEVs following the retraction of the VRT subsidy.

4.2. Governmental policy levers

The purpose of policies which act in favour of AFVs are, in general, to incentivise the sale of a new technology to a point where they overcome the initial barriers associated with purchasing and begin to achieve a greater market share. If incentives are drawn back too soon, they can prove ineffective. If incentives remain for too long, they may prove overly expensive. For this reason, 3 targets are set – achieving a 10%, 50% and 80% market share penetration. In each of these scenarios, once the market share is achieved, the subsidy is ceased. Values marked with an asterisk in Table 7 signify success in meeting this target, while other figures represent a failed target. The scenarios for this analysis are divided into both monetary policy levers – offering a derogation of VRT, VAT, AMT, and offering free fuel for AFVs – and non-monetary policy levers – banning the sale of ICEs in 2030 with a 5 year phase in period. This latter policy lever is chosen to be in line with the Irish stated national ambition that by 2030 all new cars and vans sold in Ireland will be zero emission capable (DTTAS, 2017), which roughly follows recent ambitions by France and the United Kingdom to ban the sale of petrol and diesel cars by 2040 (Department for Environment, 2017; Ministère de la Transition, 2017). An externality to the model is the number of AFV models available for sale, as both Ireland and Denmark are vehicle 'takers' rather than vehicle 'makers'. This attribute is classified into a 'low' scenario, where there is no change to the number of AFV models available, a 'medium' scenario, where by 2050 there are half of the number of AFV models available as there are currently ICEs, and a 'high' scenario, where the number of AFVs and ICE models available in 2050 is equal.

The monetary results in Table 7 represent the combined annual tax revenue foregone and cost of incentive (in the case of 'No Refuelling Costs') of that scenario relative to the BaU (see preceding section for definition). For this reason, the 'No Incentive' policy could still result in a loss to the exchequer as the taxes paid by AFV consumers are, in general, lower than that of ICEs. The percentages in Table 7 represent the WTW CO₂ emissions reduction relative to the base year.

Placing an early ban on the sale of ICEs was found to have the cost optimal impact on the uptake of AFVs, with the penetration target met in 88 of the 90 scenarios run. In the case when no incentives are offered, there is generally a loss in revenue relative to the BaU due to the relatively cheaper nature of AFVs. In the scenario without any incentive offered, a high AFV model availability and a ban on the sale of ICEs, the average annual loss in tax to the exchequer is €169.7 m/year in Ireland (resulting in an 89.3% AFV penetration) and €408.2 m/year (resulting in an 86% AFV penetration) in Denmark, where the relative higher loss in Denmark is due to the higher rates of tax. In some rare cases, there is a net gain in tax revenue (signified by a negative value in Fig. 10) due to the greater purchasing of AFVs close to the base year, when investment costs are relatively higher compared against ICEs which, in turn, yields a higher tax. In the case where no limit is placed on the sale of ICEs, the AFV target was achieved in just 25 scenario runs out of 90, with an 80% AFV penetration only met in 1 scenario (high availability of AFVs + VAT derogation in Ireland).

While all 90 scenario runs are presented in Table 7, Fig. 10 presents the market share and associated cost to the exchequer for four scenarios defined as follows:

- i. S1 – Low AFV model availability, no ban on the sale of ICEs, no further incentives offered (BaU).

Table 7
Tax foregone/cost of incentive (in million 2015€ per annum) and% WTV CO₂ emission reductions in 2050 relative to 2015.

Country	Scenario	No ban on ICE sales				Ban on ICE sales by 2030			
		Low AFV model availability	Med AFV model availability	High AFV model availability	Low AFV model availability	Med AFV model availability	High AFV model availability		
Ireland	10% AFV Target	No incentive	€0m/19.9%	€101 m/54.4%	€114.1 m/59.1%	€162.3 m/68%	€179.5 m/68.8%	€169.7 m/69.5%	
		VRT derogation	€24.2 m/20.5%	€130.9 m/54.5%	€147.1 m/59.1%	€187.7 m/68%	€207.1 m/69%	€206.9 m/69.6%	
		VAT derogation	€43.6 m/21%	€141.3 m/54.6%	€155.3 m/59.3%	€216.9 m/68.1%	€216.9 m/69.1%	€208.6 m/69.8%	
		AMT derogation	€1.5 m/20%	€145.3 m/59.1%	€163.1 m/68%	€179.6 m/68.9%	€179.6 m/69.5%	€169.8 m/69.5%	
	50% AFVs Target	No retelling costs	€6.4 m/20.6%	€102 m/54.6%	€112.9 m/59.2%	€164.5 m/68%	€178.5 m/69%	€167.7 m/69.7%	
		No incentive	€0m/19.9%	€101 m/54.4%	€114.1 m/59.1%	€162.3 m/68%	€179.5 m/68.8%	€169.7 m/69.5%	
		VRT derogation	€24.2 m/20.5%	€292.5 m/56.5%	€302.6 m/60.6%	€316.1 m/68%	€339.1 m/69.3%	€336.4 m/70%	
		VAT derogation	€43.6 m/21%	€391.5 m/57.2%	€374.2 m/61%	€399 m/68.1%	€420.9 m/69.8%	€400.8 m/70.6%	
	80% AFVs Target	No retelling costs	€6.4 m/20.6%	€110.4 m/54.7%	€121.8 m/59.3%	€168.9 m/68%	€185.2 m/68.9%	€175.1 m/69.5%	
		No incentive	€0m/19.9%	€101 m/54.4%	€114.1 m/59.1%	€162.3 m/68%	€179.5 m/68.8%	€181.6 m/70%	
		VRT derogation	€24.2 m/20.5%	€484.4 m/60%	€561.5 m/64.1%	€632.3 m/68%	€697.9 m/69.5%	€520.8 m/70%	
		VAT derogation	€43.6 m/21%	€748.7 m/62.6%	€823.8 m/65.9%	€753.5 m/68.1%	€701.7 m/69.2%	€705.8 m/70.6%	
Denmark	10% AFV Target	AMT derogation	€1.5 m/20%	€114.9 m/54.7%	€130.4 m/59.4%	€179.2 m/68%	€193.6 m/68.9%	€183.6 m/69.6%	
		No retelling costs	€6.4 m/20.6%	€154.4 m/59.6%	€173.4 m/63.7%	€211.5 m/68.1%	€219.9 m/69.4%	€206.7 m/70.1%	
		No incentive	€0m/17.6%	€16.3 m/18.7%	€19 m/18.9%	€105.8 m/76.4%	€325.9 m/76.6%	€433.8 m/76.7%	
		VRT derogation	€165.9 m/19.3%	€433.6 m/24.7%	€452.9 m/24.9%	€715 m/77.8%	€718.3 m/78.4%	€721.9 m/78.1%	
	50% AFVs Target	VAT derogation	€425.9 m/18.3%	€50.2 m/19.1%	€66.8 m/19.7%	€402.4 m/76.6%	€494.9 m/77%	€592.6 m/77.1%	
		AMT derogation	€0.9 m/17.6%	€16.6 m/18.7%	€19.4 m/19%	€108.6 m/76.4%	€326.7 m/76.6%	€434.5 m/76.7%	
		No retelling costs	€3.7 m/17.7%	€16.3 m/18.7%	€16.6 m/19%	€296.3 m/76.4%	€465.9 m/76.7%	€555.7 m/76.7%	
		No incentive	€0m/17.6%	€16.3 m/18.7%	€19 m/18.9%	€105.8 m/76.4%	€325.9 m/76.6%	€433.8 m/76.7%	
	80% AFVs Target	VRT derogation	€165.9 m/19.3%	€1,761.7 m/51.6%	€1,865.3 m/53%	€1,862 m/77.8%	€1,462.7 m/81%	€1,475.3 m/81.3%	
		VAT derogation	€425.9 m/18.3%	€50.2 m/19.1%	€66.8 m/19.7%	€389.8 m/76.6%	€705.4 m/77.1%	€766.2 m/77.2%	
		AMT derogation	€0.9 m/17.6%	€16.6 m/18.7%	€19.4 m/19%	€108.6 m/76.4%	€326.1 m/76.7%	€434.5 m/76.7%	
		No retelling costs	€3.7 m/17.7%	€16.3 m/18.7%	€16.6 m/19%	€274.7 m/76.4%	€444.2 m/76.7%	€533.9 m/76.7%	
80% AFVs Target	No incentive	€0m/17.6%	€16.3 m/18.7%	€19 m/18.9%	€105.8 m/76.4%	€325.9 m/76.6%	€433.8 m/76.7%		
	VRT derogation	€165.9 m/19.3%	€2,009.1 m/59.5%	€2,323.8 m/65.4%	€2,219 m/77.7%	€2,378.3 m/81.3%	€2,418.8 m/81.7%		
	VAT derogation	€425.9 m/18.3%	€50.2 m/19.1%	€66.8 m/19.7%	€797.1 m/76.6%	€924.7 m/77.1%	€1009.2 m/77.3%		
	AMT derogation	€0.9 m/17.6%	€16.6 m/18.7%	€11.4 m/19%	€330.9 m/76.7%	€438.7 m/76.7%	€488.7 m/76.7%		
		No retelling costs	€3.7 m/17.7%	€16.6 m/19%	€222.1 m/76.4%	€383.1 m/76.7%	€475.9 m/76.7%		

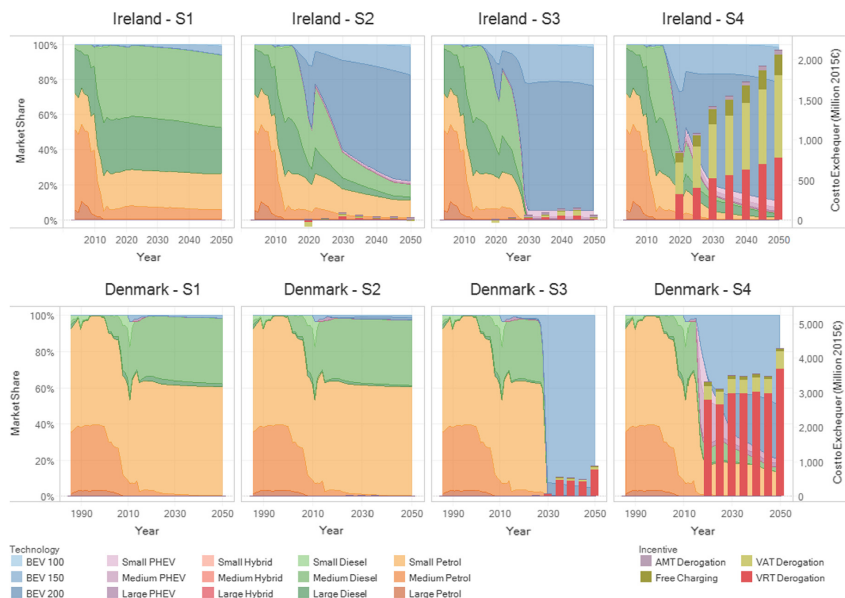


Fig. 10. Market Share and annual cost to the Exchequer for select scenarios from the consumer choice model.

- ii. S2 – High AFV model availability, no ban on the sale of ICEs, no further incentives offered.
- iii. S3 – Medium AFV model availability, ban on the sale of ICEs in 2030, no further incentives offered.
- iv. S4 – Medium AFV model availability, no ban on the sale of ICEs, derogation of VAT, VRT, AMT, and no refuelling costs.

S1 in both countries represents the initial question aimed at in this study – what will be the effect of the VRT subsidy retraction. The other question posed by this study, which focused on the cost and effect of further incentivisation of AFV purchasing, are answered in scenarios S2 through S4. The high costs associated with the Danish VRT tax system creates great difficulty in a penetration of AFVs in S2, where the disutility from model availability is largely reduced due to an increase in the number of AFVs available for sale. In the same scenario in Ireland, while the VRT subsidy retraction for BEVs causes a drop off in market sales in 2022, BEVs start to emerge strongly in the market through to 2050. In S3, whereby a ban is placed on the sale of ICEs, and there are half as many AFVs available for sale in 2050 as ICEs, a much faster emergence of AFVs is seen, although the Danish government start to face large drops in revenue from VRT and VAT tax foregone, amounting to €1.1 billion Euros in 2050 alone. Finally in the most costly scenario, S4, where there is no ban on the sale of ICEs, and there is a derogation of VRT, VAT, AMT, and no refuelling costs, there is a fast uptake of AFVs in both Ireland and Denmark, yet this comes at a significant cost to the exchequer, €4.3 billion in Denmark and €2.1 billion in Ireland in 2050.

5. Conclusions and policy recommendations

It is both challenging and expensive to electrify the private transport sector in Ireland and Denmark. To arrive at this conclusion, this study has created a socio-economic consumer choice model which accounts for the costs and disutilities of 15 technologies available to Irish and Danish consumers and linked it with a simulation model of the Danish and Irish private vehicle sector. The purpose of the study is to identify the effect of the currently planned retraction of the vehicle registration tax (VRT) subsidy in Ireland and Denmark, and to assess at what cost and level of effectiveness further incentives may aid in promoting the sale of low carbon vehicles.

In line with these aims, the study finds that retracting the VRT subsidies in accordance with both Irish and Danish national policies will result in a low penetration of alternative fuelled vehicles (AFV) through to 2050. This is especially true in Denmark where there is currently a very generous VRT subsidy, despite the expected decrease in capital costs of battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) (a combined 4.5% market share in Ireland in 2050, up from 0.39% in 2015 and 1.7% in Denmark in 2050, up from 1.6% in 2015).

A high penetration of AFVs in both countries was achieved through placing a ban on the sale of internal combustion engine (ICE) vehicles by 2030, although this comes at a loss to the exchequer in the form of tax foregone as AFVs, in general, are expected to cost less than ICEs in the future and therefore bring in less tax. Placing this ban achieves over an 80% penetration of AFVs by 2050 and comes at an opportunity cost through tax foregone in the range of €162–170 m/year for Ireland and €106–434 m/year for Denmark, dependent on the availability of AFV models for sale. Without regulating the sales of ICEs, Ireland could still achieve a substantial market penetration through a derogation of VAT on AFVs, but this comes at a higher average opportunity cost of €826 m/year. This same market penetration was found to be impossible through single incentives in Denmark, although a combination of VRT and VAT derogation on AFVs provided an 86% stock share by 2050 at an average loss to the exchequer of €3.6b/year.

This challenge and high cost of electrifying private transport is largely due to the number of high disutility costs preventing a large market penetration, but in particular due to the disutility cost associated with the low number of models of BEVs and PHEVs currently available for sale relative to ICEs. Moreover, this is impossible to be overcome through national policy interventions in Ireland or Denmark, as neither country produces automobiles, while their cumulative demand of vehicles is quite low relative to all of Europe, accounting for approximately 2.5% of all European vehicle sales (EEA, 2017). A European wide policy focusing on increasing the number of AFV models available, such as the Zero Emission Vehicle Program adopted by 9 states in the US (CARB, 2009), may be necessary to overcome this barrier whereby manufactures are mandated to sell AFVs.

Further work to this study would include a more thorough analysis of the vehicle market. This study assumed the number of ICEs available for sale did not change from the base year (with the exception of the ban placed on the sale of such vehicles) although in reality the market has a tendency to fluctuate based on a variety of factors. This study is also constrained by the number of behaviour attributes considered within this modelling framework. While this study modelled the intangible costs from model availability, risk related disutility, range anxiety, and refuelling/recharging infrastructure availability, there are a plethora of other preferences which consumers may have when purchasing a vehicle that are outside of the scope of this study.

Competing interests

The authors have no competing interests to declare.

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Appendix A

Table 8.

Table 8
Resulting market share of AFVs and ICEs in 2050 from sensitivity analysis of variance factor, v_a , for the BaU.

Variance factor, v_a	Ireland		Denmark	
	AFV market share	ICE market share	AFV market share	ICE market share
15	6.1%	93.9%	3.3%	96.7%
10	8.4%	91.6%	3.2%	96.8%
20	5.4%	94.6%	3.5%	96.5%

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.trd.2018.04.010>.

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Glossary

- ICE: Internal combustion engines
- WTW: Well-to-Wheel
- MNL: Multinomial logit
- CO₂: Carbon dioxide
- BEV: Battery electric vehicle
- PHEV: Plug in hybrid electric vehicle
- VRT: Vehicle registration tax
- VAT: Value Added Tax
- AMT: Annual Motor Tax
- AFV: Alternative Fuelled Vehicle
- SPS: Stated Preference Survey
- LCC: Life Cycle Cost
- GNP: Gross National Product

**A LONG-TERM STRATEGY TO
DECARBONISE THE DANISH
INLAND PASSENGER TRANSPORT
SECTOR**

A Long-Term Strategy to Decarbonise the Danish Inland Passenger Transport Sector



Jacopo Tattini, Eamonn Mulholland, Giada Venturini,
 Mohammad Ahanchian, Maurizio Gargiulo, Olexandr Balyk
 and Kenneth Karlsson

Key messages

- Danish decarbonisation target is in line with an increase in global temperatures of 1.75–2 °C
- Early ban on Internal Combustion Engines (ICE) allows the largest decrease in cumulative emissions from Danish transport sector
- Early ban on ICE generates the highest tax revenue for the exchequer
- The innovative modelling framework that links a national optimization energy system model with a private car simulation model provides consumer realism to study the decarbonisation of the inland transport sector.

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137

1 Introduction

The 21st meeting of the Conference of Parties (COP21) witnessed an agreement to pursue efforts to limit temperature increase to 1.5 °C above pre-industrial levels (UNFCCC 2016) through Intended National Determined Contributions (INDCs). Limiting global temperature rise to 1.5 °C above pre-industrial levels relates to a total carbon budget of between 400 and 850 GtCO₂ eq (as of 2011) with the respective probability of achievement varying between >66 and >33% (IPCC 2014). While each signatory of the COP21 agreement will play a varied role in adhering to these carbon budgets, there has yet to be an agreement for the equitable sharing of national carbon budgets. This chapter creates a range of provisional carbon budgets for Denmark and focuses on the potential of policies aimed at the inland transport sector compliance with these budgets. Denmark is chosen as a case study following the ambitious target set by the Danish government to decarbonise the entire energy system by 2050 (The Danish Government 2011). Furthermore, the inland transport sector is given focus considering that its share amounted to 28% of the total energy consumption in 2015 (Eurostat 2017). So far, attempts to encourage renewables within the transport sector have been largely offset by an increase in transport activity and a lack of alternatives available. Significant levels of policy intervention are required to reduce the transport sector reliance on fossil fuels. The study aims at determining the contribution of policies to decarbonise the inland passenger transport sector and to calculate national cumulative greenhouse gas (GHG) emissions, which are compared to a range of carbon budgets necessary to contribute to limit global temperature rise. This chapter aims at answering the following research questions:

1. How much GHG emissions reduction can be achieved in Denmark through policies focusing on inland passenger transport?
2. Will the cumulative GHG emissions up to 2050 exceed the carbon budget available for Denmark to maintain the average global temperature rise well below 2 °C?

An innovative modelling framework is adopted, which links a techno-economic energy systems optimisation model of Denmark—TIMES-DKMS—with a hybrid techno-economic and socio-economic simulation of the Danish private car sector—the Danish Car Stock Model (DCSM)—to provide realistic answers to the research questions underlying this study. The transport sector within TIMES-DKMS features endogenous modal shift. DCSM represents the heterogeneous nature of the private car sector. A variety of policy packages aimed at reaching an ambitious decarbonisation of the inland transport sector are implemented iteratively in both TIMES-DKMS and the supporting simulation models.

2 Methodology

This study is carried out with an original modelling framework, which integrates TIMES-DKMS—the national energy system model of Denmark equipped with modal shift add-on (Tattini et al. 2018a)—with DCSM—a consumer choice model of the private transport sector accompanied by a sectoral simulation model of the private car sector.

2.1 *TIMES-DKMS*

TIMES-DKMS is built on the TIMES (The Integrated MARKAL EFOM System) model generator, developed by the Energy Technology Systems Analysis Program (ETSAP)—a technology collaboration programme of the International Energy Agency (IEA). It is a partial equilibrium, linear optimisation model, which determines a least-cost solution for the energy system, subject to certain constraints. TIMES performs a simultaneous optimisation of operation and investments across the represented energy system over the modelling horizon. TIMES is based on the bottom-up approach, as it requires a database of technologies characterised by a high technical, economic and environmental detail. Loulou et al. (2016) provide a detailed description of TIMES.

TIMES-DKMS is a multi-regional TIMES model, covering the entire Danish energy system. It is geographically aggregated into two regions, with technological and economic projections to 2050. TIMES-DKMS is composed of five sectors: supply, power and heat, transport, industry and residential (Balyk et al. 2018). Within the scope of this study, we focus on inland passenger transport, which includes private car, bus, coach, rail (metro, train, S-train), 2-wheeler (motorcycle and moped) and non-motorized modes (bike and walk). Within the inland passenger transport sector, TIMES-DKMS determines modal shares endogenously. The mode- and length-specific transport service demands are merged into length-only specific transport service demands, thus enabling competition between modes. Modal competition is based on both the levelised costs of the modes and on new parameters in the TIMES framework: speed and infrastructure requirements. Modal speeds are complemented by a constraint on the total travel time budget (TTB), historically observed for the Danish transport sector (Transport DTU 2016). The TTB ensures the competitiveness of faster yet more expensive modes in a cost-optimisation modelling framework. Infrastructure accounts for the cost of adapting the existing transport networks to demand increases and possible significant modal shift. Infrastructure requirements regulate modal shift, as this may end up in infrastructure saturation, subsequently requiring additional infrastructure capacity, which implies a cost (Tattini et al. 2018a). Moreover, constraints on the maximal and minimal modal shares and on the rate of shift derived from the Danish National Travel Survey are included in TIMES-DKMS to guarantee the realism of

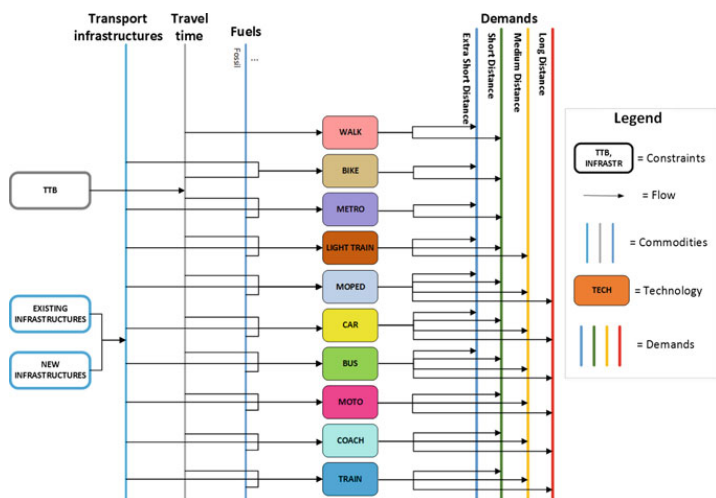


Fig. 1 Structure of the inland passenger transport sector in TIMES-DKMS for incorporating modal shift

the shift. Tattini et al. (2018a) provide a detailed description of TIMES-DKMS. Figure 1 provides a schematic description of the structure of TIMES-DKMS.

TIMES-DKMS outputs the least-cost decarbonisation pathway that meets all the constraints included in the model. However, the description of the private car sector in TIMES-DKMS is purely techno-economic, and does not account for heterogeneity within the private car market, thus suggesting a solution that may not be technically feasible (Mulholland et al. 2017a; Daly et al. 2011).

2.2 Danish Car Stock Model—DCSM

DCSM is a simulation model composed of two core components; a socio-economic consumer choice model and a techno-economic CarSTOCK model. DCSM checks the feasibility of the vehicle portfolio deployment pattern identified by TIMES-DKMS and introduces the necessary adjustments (as described in Sect. 2.3).

2.2.1 Consumer Choice Model

The consumer choice model estimates the influence of various policies on the Danish private vehicle market via a simulation market share algorithm, which has also been employed in the CIMS hybrid energy-economy model (Rivers and Jaccard 2005). This algorithm uses the tangible costs (investment cost, maintenance costs, fuel cost and vehicle-related taxes) along with a monetised representation of the intangible costs (model availability, range anxiety, and refuelling infrastructure) faced by the consumers to calculate the market share of a technology in a specific year when competing against a set of technologies. Heterogeneity of private vehicle preferences are accounted for through splitting transport users into 18 segments, divided geographically (urban/rural), by driving profile (Modest Driver, Average Driver, Frequent Driver) and by adoption propensity (Early Adopter, Early Majority, Late Majority), inspired by McCollum et al. (2017). Five technologies split into three categories are represented in the model—gasoline internal combustion engine (ICE), diesel ICE, natural gas (NG) ICE, battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) disaggregated into the classes small, medium, and large (for ICEs, based off engine size) and into short, medium, and long range for BEVs (<125, 125–175, >175 km respectively). Mulholland et al. (2017b) provide a further description of the market segmentation and of the tangible and intangible costs for Denmark. The consumer choice model generates the market shares of the vehicle stock and outputs this result to the CarSTOCK model to determine the impact of policy measures on aggregate stock.

2.2.2 CarSTOCK Model

CarSTOCK is a bottom-up model that uses the outputs of the consumer choice model to create stock projections and analyse the net effect of policy measures in Denmark (Mulholland et al. 2017b). The CarSTOCK model draws upon detailed Danish statistics (FDM 2017), relating to the composition of private car sales, average mileage, efficiency, and life-time of vehicles with a disaggregation of vintage, fuel type and engine size (vehicle range in the case of BEVs). Using these inputs, it determines the long-term evolution of the private car stock, energy use and related CO₂ emissions to 2050 based off the ASIF methodology developed by Schipper et al. (2000). Total vehicle stock resulting from TIMES-DKMS is fed to CarSTOCK, which combines private car profiles and market shares (from the consumer choice model) to calculate the market shares of each car type with respect to total car stock. The CarSTOCK model has a detailed disaggregation of private car technologies into technology type (in line with those described in the Consumer Choice Model) and 30 vintage categories to represent the evolution of the car fleet.

2.3 Multi-model Approach

Integrating models has become an increasingly common approach in the field of energy system modelling (Mulholland et al. 2017a; Merven et al. 2012; Schäfer and Jacoby 2005). In the modelling framework used here, the policy measures are run in both the consumer choice model and in TIMES-DKMS in parallel. TIMES-DKMS first determines the optimal technology investments to meet the exogenous end-use demands at the least overall systems cost. Then, DCSM checks the technical feasibility of the solution obtained with TIMES-DKMS for the private passenger transport sector. If the solution is not feasible, capacity constraints bounding the stock of specific car technologies are added in TIMES-DKMS to comply with the realistic car shares projections calculated by the CarSTOCK model. A new solution is obtained with TIMES-DKMS, which is again verified in DCSM. Data exchange between the two models is iterated until there is convergence between the results (Fig. 2).

To ensure consistency within the model framework, the private vehicle costs in TIMES-DKMS and DCSM are harmonised for 2015 (Fig. 3). The road infrastructure cost is omitted from Fig. 3, as it is identical for all car types. Upon including the intangible costs in DCSM, the merit order of the car technologies changes compared to an analysis limited to tangible costs. This suggests that DCSM offers a more comprehensive view on the characteristics of cars perceived by consumers. Therefore, the multi-model approach employed in this study benefits from the models' respective strengths: the holistic representation of the integrated Danish energy system and the behaviourally-detailed insight of the Danish car consumer choice.

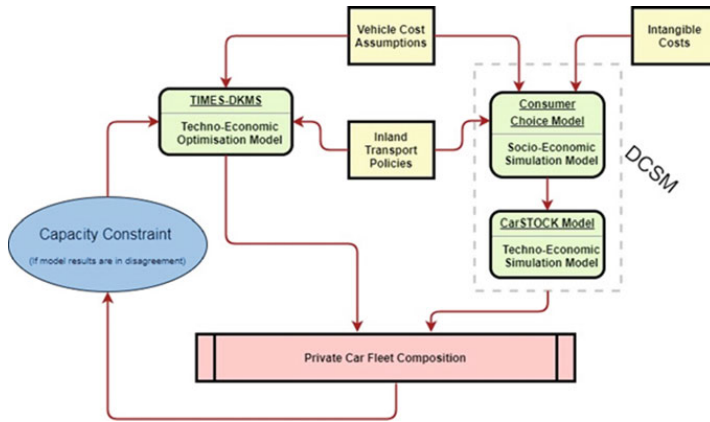


Fig. 2 Model integration between TIMES-DKMS and DCSM

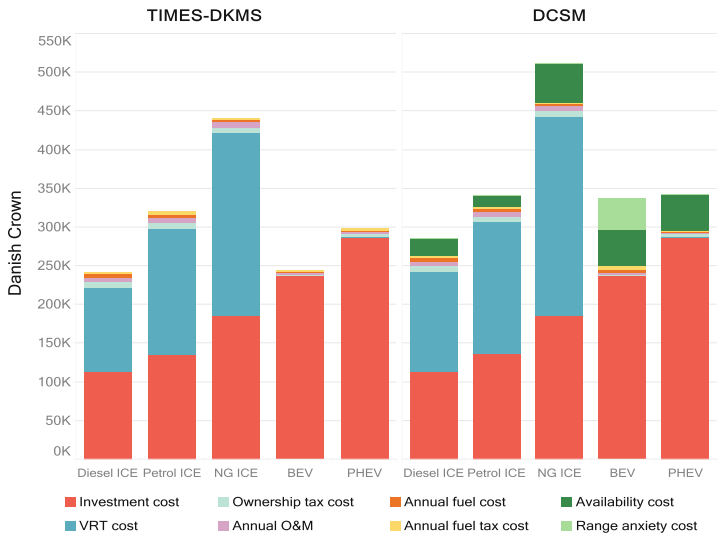


Fig. 3 Comparison of tangible and intangible costs in 2015 in TIMES-DKMS and DCSM

2.4 Carbon Budget for Denmark

This study allocates a carbon budget for Denmark based on population (‘equity’) and emissions (‘inertia’), following the approach proposed by Raupach et al. (2014). To establish the carbon budget for Denmark, the global carbon budgets required to limit global temperature rise to varying levels with varying probabilities of achievement are taken from the 5th Assessment Report by IPCC (2014), which uses a base year of 2011. Denmark’s national share is calculated using emission data from UN (2017a) and population data from UN (2017b). This national budget is brought up to a base year of 2015 using emissions data from UN (2017a). Land use and land use change and forestry (LULUCF) related emissions are subtracted using data from CDIAC (2016), resulting in the range of carbon budgets for the Danish energy system presented in Table 1.

2.5 Scenario Definition

In this study, we analyse the potential reduction of GHG emissions in Denmark enabled by alternative developments of the vehicle registration tax (VRT), the fuel

Table 1 Carbon budgets for the Danish energy system from 2015 corresponding to different levels of global temperature rise and levels of confidence [MtCO₂ eq]

Temperature rise/confidence level	66%	50%	33%
4 °C target	3438	4031	4562
3 °C target	2090	2499	2958
2.5 °C target	1375	1733	2065
2 °C target	660	967	1171
1.5 °C target	48	201	507

Table 2 Description of scenarios for the policy analysis

Scenario	Description
Ref	Reference scenario, only 2020 targets included
Fuel tax	The tax paid on electricity used for transport, equal to 245.8 DKK/GJ in 2015, is derogated from 2020 onwards
VRT	The Vehicle Registration Tax (VRT) is derogated for all electric, hybrid and hydrogen vehicles from 2020 onwards
Fuel tax and VRT	Combination of the scenarios Fuel Tax and VRT
ICE bans	A ban on the purchase of new ICE cars is introduced from the year 2025, 2030, 2035 or 2040 (i.e. four scenario variants)

tax and from banning the sale of ICE vehicles in different years (Table 2). Denmark taxes cars through a *VRT* based on the capital cost and fuel efficiency of the vehicle, through a *circulation tax* based on the efficiency and weight of the vehicle and through *fuel taxes*. The *VRT* scenario assesses the effect of the derogation of the VRT for BEV and PHEV from 2020 onwards. In the *Fuel Tax* scenario, the tax on electricity used in transport is lifted from 2020 onwards, while keeping all other fuel taxes constant. In the *Fuel Tax and VRT* scenario, we examine the combined effect of the VRT derogation with removing the fuel tax on electricity from 2020. Some countries are currently discussing banning the sales of ICE vehicles in the near future (International Energy Agency 2017), which justifies the interest in analysing the effects of banning ICE cars sales.

All policy scenarios are consistent with Denmark's target of becoming independent from fossil fuels by 2050 (Danish Energy Agency 2015). This constraint is set on all sectors represented in TIMES-DKMS, with the exception of inland transport, for which the policies under assessment are the only option to reach the decarbonisation. Moreover, short- and medium-term targets complying with the European objective of minimum 10% renewable energy share in transport by 2020 and a 39% GHG emission reduction in 2030 with respect to 2005 levels (European Commission 2016) are applied. The policy scenarios are compared against a

reference scenario (*Ref*), which maintains only the short-term targets for 2020, i.e. minimum 10% renewable energy share in transport and 50% electricity production from wind power.

3 Results: Focus on Technologies

3.1 Evolution of the Car Stock

The *Ref* scenario is characterised by a minor penetration of EVs, which represent 2.5% of the total car stock in 2050 (Fig. 4). The policies modelled boost the penetration of EVs with different degrees of effectiveness. The derogation of the tax on electricity for transport does not foster a strong penetration of EVs, while a derogation of the VRT on EVs enables a significant electrification of the car stock by 2050 (24% of car stock). The combined effect of fuel tax and VRT derogation accelerates the process of electrification of the car stock (32% in 2050). Setting a ban on the sale/import of vehicles run solely by an ICE strongly promotes the total electrification of the car stock. In the *ICE_Ban_2040* scenario, 93% of the stock is electric in 2050, while in *ICE_Ban_2035* scenario the entire stock becomes electric in 2050. The complete electrification of the car stock is anticipated by 2045 in the *ICE_Ban_2030* scenario and by 2040 for *ICE_Ban_2025*. Among EVs, PHEV

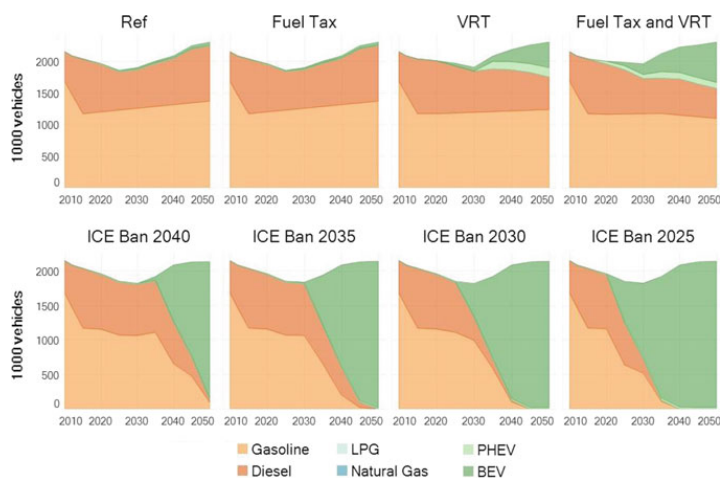


Fig. 4 Evolution of the car stock and car technologies in time across scenarios in TIMES-DKMS

technology only reaches a significant share of the total stock in the VRT scenario (6.5% in 2050), which demonstrates that the major barrier to the wide deployment of this technology is its high investment cost.

3.2 Modal Shares for Inland Passenger Transport

In most policy scenarios, the car stock decreases over the period 2020–2030 due to the increase in the average cost of ICE vehicles to fulfil the more stringent EU fuel standards concurrent with stagnant alternative fueled vehicle (AFV) costs. These have not decreased enough as to become a widely accepted technology, prompting a modal shift to public buses, which is a cheaper option (Fig. 5). After 2035, BEVs achieve a significant cost reduction due to the decrease in battery costs and cars gain again a higher modal share at the expense of public buses. In 2050, across all policy scenarios, bike, coach, metro, S-train and train modes increase their market share with respect to 2010, at the expense of transport by bus, car, 2-wheeler and walk. In particular, bike and metro transport witness the highest increment of use with respect to 2010.

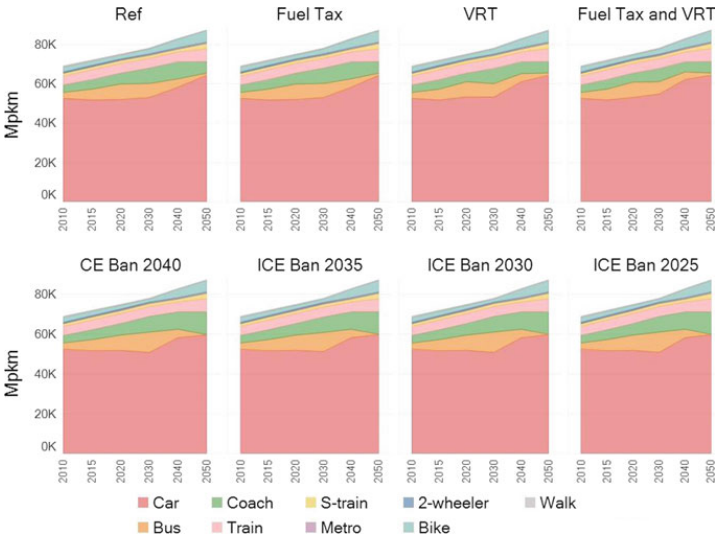


Fig. 5 Modal shares across scenarios in TIMES-DKMS

3.3 Fuel Mix for Inland Passenger Transport

The combined consumption of diesel and bio-diesel increases until 2020 in the *Ref* scenario, and then decreases by 2050 following improvements in fuel-economy and fuel switching, predominantly to electricity (Fig. 6). The share of bio-diesel in the blend gradually increases until reaching 72% in 2050. The combined consumption of gasoline and bio-ethanol decreases over time, while the share of bio-ethanol in the blend increases from 5.8% in 2015 to 45.4% in 2050. Moreover, electricity acquires a higher importance as fuel, constituting 5.3% of the total inland passenger transport fuel consumption in 2050. The drop in fuel consumption in 2030 is a consequence of multiple factors: a shift away from cars towards buses (characterised by a lower relative energy-intensity), an electrification of the car stock and efficiency improvements.

The fuel consumption varies across scenarios, due to changes in modal shares and technology shares within the car stock (Fig. 7).

In all the policy scenarios, with the exception of *Fuel_Tax*, the total fuel consumption reduces in 2050 with respect to the *Ref* scenario. Placing a ban on ICE vehicles causes reduction in fuel consumption due to the switch to electric vehicles (EVs), which have a significantly higher fuel economy than their ICE counterpart. It should also be noted that the private car sector has a major impact on total fuel consumption from the perspective of the inland passenger transport sector, illustrated by the similarities between the variations in car stock (Fig. 4) and fuel consumption (Fig. 7).

3.4 GHG Emissions

The annual GHG emissions from inland passenger transport sector undergo a significant decrease over time across all scenarios (Fig. 8). GHG emissions in 2050 drop by 37.3% in the *Ref* scenario with respect to 2010, due to a penetration of biofuels, EVs, and increases in the average efficiency of vehicles. These reductions are achieved despite the overall increase of transport activity over the same period.

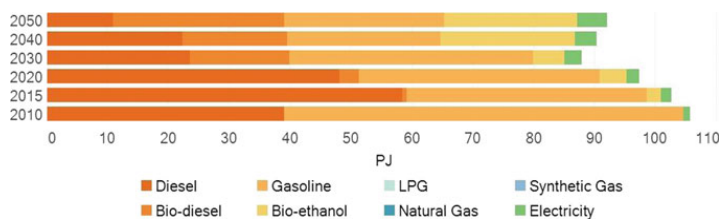


Fig. 6 Fuel consumption from inland passenger transport in Ref scenario

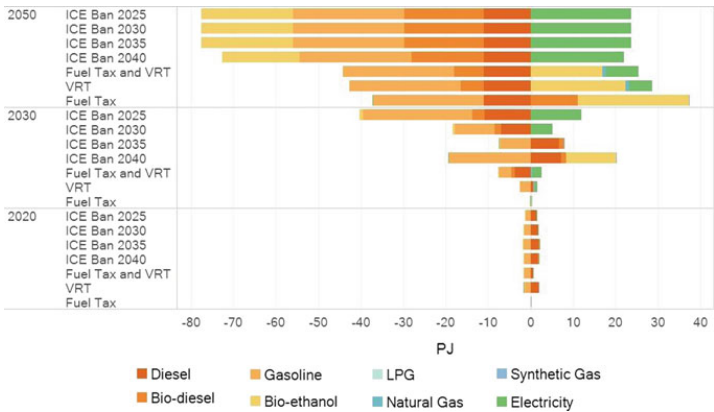


Fig. 7 Difference in fuel consumption from inland passenger transport across policy scenarios with respect to the Ref scenario

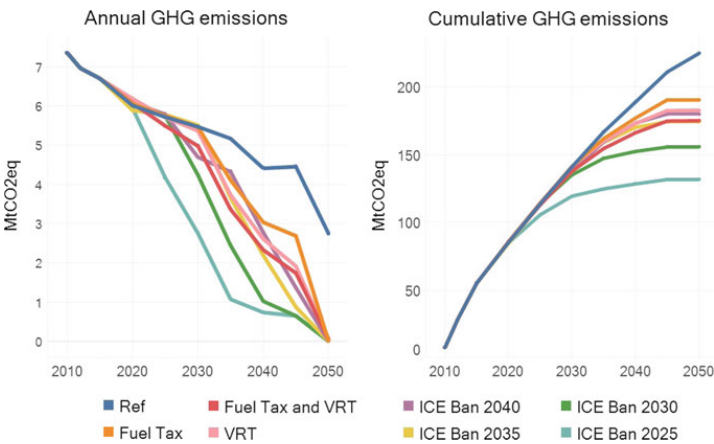


Fig. 8 Annual (left side) and cumulative (right side) GHG emissions from inland passenger transport sector

The implementation of transport policies enables the achievement of more ambitious decarbonisation targets. The inland passenger transport sector is completely decarbonised by 2050 in the *Fuel_Tax* scenario and all scenarios that include an ICE ban. The greatest cumulative reduction in GHG emissions is achieved through

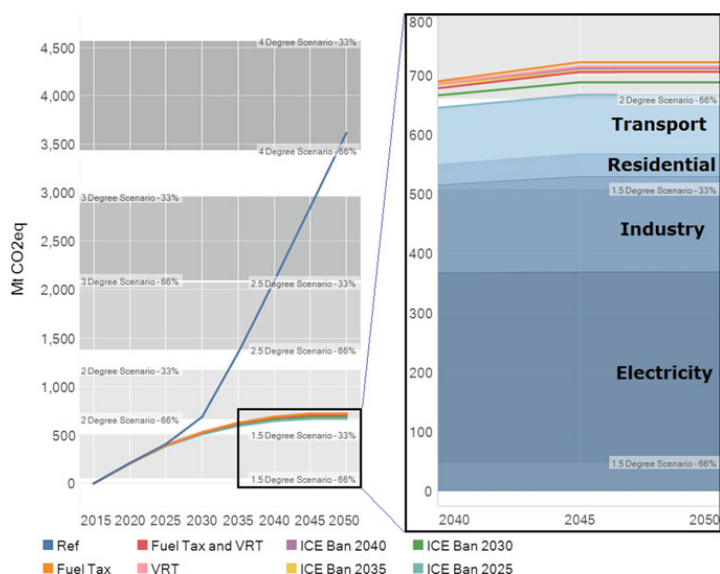


Fig. 9 Cumulative GHG emissions from the entire Danish energy system

an early ban placed on ICE vehicles (in 2025 and in 2030), while taxation-focused policy has a similar effect to that of later bans (in 2035 and 2040).

Figure 9 extends the focus of the analysis from inland passenger transport to the entire Danish energy system, showing the cumulative GHG emissions of the energy system over the modelled time horizon. In the *Ref* scenario, the cumulative GHG emissions diverge from the policy scenarios from 2025, and in particular, the steepness of cumulative GHG emissions increases after 2030 due to the adoption of coal-fired plants for power generation. In the policy scenarios, GHG emissions gradually decrease over time, to comply with the Danish environmental target of becoming fossil-free by 2050. Granted a fossil-free energy system is achieved in all sectors excluding inland passenger transport, the policy scenarios indicate that cumulative GHG emissions from the entire Danish energy system in 2050 are in line with a national contribution of an increase in global temperatures of 1.75–2 °C (excluding the possibility of negative emissions in the second half of the century). Figure 9 also shows the contribution of each energy sector towards national cumulative GHG emissions for the *ICE_Ban_2025* scenario, with the marginal emissions for the inland passenger transport scenarios shown above these contributions. The electricity sector is accountable for half of all emissions over the time-frame 2015–2050, matching those from the residential, industry, and transport sectors combined.

4 Discussion: Focus on Lessons Learned

4.1 Policy Insights

This study has analysed a range of regulatory measures focused on inland passenger transport while simultaneously decarbonising the rest of the energy system at least-cost. A central focus has been given to the potential of these measures to minimise cumulative GHG emissions to adhere to national carbon budgets. While evaluating the potential outcome of transport policies, it is important to consider not only their effectiveness, but also their efficiency, which can be evaluated as difference in actualised tax revenue with respect to the *Ref* scenario. The effect of policies on the tax revenue shows that *Fuel Tax and VRT* implies the highest loss of revenue for the exchequer (Fig. 10). The 6.2% reduction for *Fuel Tax and VRT* is explained by the uptake of BEV and PHEV from 2020, upon which no VRT and tax on electricity consumption are imposed. On the other hand, the *ICE_Ban* scenarios enforced from 2035 onwards benefit the tax revenues, due to the penetration of taxed AFV when their investment costs have not dropped yet.

Although from an environmental and tax revenue perspective, the *ICE_Ban_2025* is the most effective of all policies analysed, the different degrees of feasibility of policy instigation should be considered, stemming from their different timing, method of implementation, and public acceptability. Changes to taxation schemes require several government consultations while the introduction of a ban of ICEs presents a challenge in terms of negotiations (on timing and exceptions) with the automotive industry, let alone the preferences of consumers. While identifying the early ban on the sale of ICE as a suitable policy to decarbonise the Danish inland passenger transport sector, we recognise the lack of comprehensiveness of the policy measures analysed, e.g. measures affecting modal shift have not been addressed (Tattini et al. 2018b).

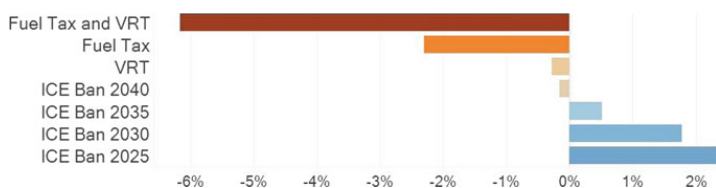


Fig. 10 Actualised cumulative change in tax revenue with respect to the Ref scenario

4.2 Methodology Insights

The adopted model framework improves the representation of the transport sector compared to traditional bottom-up energy systems optimisation models. Modal shift provides an additional option to explore decarbonisation pathways, and realistic consumer preferences in the private car sector are accounted through to the integration of the DCSM. However, there are still some limitations that future research may address. One limitation relates to the fact that TIMES-DKMS results do not take into account that even with a ban on ICE vehicles in 2025, there would still be some ICE vehicles circulating in 2050 according to DCSM (without any incentive for early scrapping). Modal shares are determined only via a suitably constrained socio-economic optimisation. A possible way to overcome this shortcoming consists of integrating consumers' heterogeneity into the model (differentiating their travel habits, perceptions and thus preferences) and determining modal shares resulting from a set of decisions taken by diverse consumers. Moreover, the level-of-service attributes characterising the modes should go beyond speed, to include also other relevant ones, e.g. waiting time and transfer time (Tattini et al. 2018b). Finally, while this study has calculated potential national carbon budgets based on a combination of equity and inertia sharing, these budgets will not be fully effective unless there is a global agreement on the method for allocating national and regional carbon budgets.

5 Conclusion

This study developed an innovative multi-model approach for Denmark that integrated an energy systems optimisation model (TIMES-DKMS) with a simulation model of the private car sector (DCSM) to assess the influence of various policy measures on the decarbonisation of the inland transport sector of Denmark. The multi-model approach developed combines the strengths of both modelling methods and provides a greater degree of consumer realism to the analysis of the private car sector. The analysis of potential contribution of seven policy measures towards the decarbonisation of the Danish inland transport sector revealed that a ban on the sale of ICE cars in 2025 enables the largest decrease in GHG emissions, i.e. 41% reduction of cumulative GHG emissions from the inland passenger transport sector with respect to the reference scenario. Moreover, the ICE ban in 2025 generates the highest tax revenue for the exchequer among the scenarios analysed. Regulatory measures focused on the derogation of tax have a lower relative effect on cumulative GHG emissions reduction and have a net negative impact on tax revenue when compared against the baseline. Nonetheless, all scenarios have a significant level of decarbonisation by 2050, with a complete decarbonisation of inland passenger transport in all scenarios where a ban on the sale of ICEs was imposed, and a greater than 90% reduction relative to 2015 in policies focused on tax derogation.

A broader analysis focusing on the entire energy system revealed that neither a total derogation of VRT and fuel tax for EVs nor an early ban on the sale of ICE vehicles would not contribute to maintaining the increase of global temperature limited to 1.5 °C.

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**THE NORDIC ELECTRIC VEHICLE
OUTLOOK 2018 - INSIGHTS FROM
LEADERS IN ELECTRIC MOBILITY**

Nordic EV Outlook 2018

The Nordic region is at the forefront of the global growth of electric mobility. The *Nordic Electric Vehicle Outlook 2018 (NEVO 2018)* aims to identify and discuss recent developments of electric mobility in the five Nordic countries: Denmark, Finland, Iceland, Norway and Sweden. The report assesses the current status of the electric car market, the deployment of charging infrastructure, and the integration with the electricity grid at country level. It analyses the role of European, national, and local policy frameworks in supporting these developments. The analysis also provides insights on consumer behaviour and includes an outlook on the progress of electric mobility in the Nordic region up to 2030.

NEVO 2018 has been developed in co-operation between the International Energy Agency (IEA) and Nordic Energy Research. It builds on the long-standing IEA engagement in the area of electric mobility, including the co-ordination of the Electric Vehicles Initiative (EVI) and the hosting of the Hybrid and Electric Vehicle Technology Collaboration Programme.

<https://webstore.iea.org/nordic-ev-outlook-2018>

Abbreviations and units

AB	Agent-based
ABMoS-DK	Agent Based Modal Shift model for Denmark
AFV	Alternative fuelled vehicle
AMT	Annual motor tax
BaU	Business as Usual
BEV	Battery Electric Vehicle
BU	Bottom-up
BY	Base year
CES	Constant elasticities of substitution
CO ₂	Carbon Dioxide
CO ₂ eq	Carbon Dioxide equivalent
DCSM	Danish Car Stock Model
DKE	Denmark East
DKW	Denmark West
E3	Energy-economy-environment
E4	Energy-economy-environment-engineering
ETSAP	Energy Technology Systems Analysis Programme
EV	Electric Vehicle
GHG	Greenhouse-gas
GNP	Gross national product
H	Hybrid
IEA	International Energy Agency
ICE	Internal combustion engine
L	Long distance range
LoS	Level-of-service
LTM	Landstrafikmodellen (Danish National Transport Model)
M	Medium distance range
Maas	Mobility-as-a-service
MNL	Multinomial logit model
MoCho-TIMES	Modal Choice in TIMES
Mpkm	Million passenger kilometre
NG	Natural Gas
NMNL	Nested multinomial logit model

O&M	Operation and maintenance
OD	Origin-Destination
OECD	Organization for Economic Co-operation and Development
OEM	Original equipment manufacturer
PHEV	Plug-in Hybrid Electric Vehicle
Pkm	Passenger-kilometre
RQ	Research question
S	Short distance range
TD	Top-down
TIMES	The Integrated MARKAL EFOM Sysyem
TIMES-DK	TIMES model of Denmark
TIMES-DKEMS	TIMES model of Denmark with elastic modal shift
TIMES-DKMS	TIMES model of Denmark with modal shift
TTB	Travel Time Budget
VAT	Value added tax
VoT	Value-of-time
VRT	Vehicle registration tax
WP	Work package
XS	Extra short distance range

Both technological and behavioural changes are required to reduce the carbon intensity and energy demand of the transportation sector. Energy-economy-environment-engineering (E4) system models are a valuable tool for long-term energy planning, but are generally weak at representing human behaviour. This PhD thesis fills this gap by developing several methodologies that improve the representation of consumers' choice in transport within bottom-up (BU) optimization E4 models. The novel methodologies proposed inaugurate the possibility to analyse in a unique modelling framework that includes the entire energy system decarbonisation pathways considering technological improvements in combinations with changes in travel behaviour. The results of the analyses carried out with the novel methodologies indicate that modal shift potentially has a positive contribution to the decarbonisation of the Danish energy system. Moreover, car transport is likely to maintain the highest modal share also in the future, suggesting that modal shift should be accompanied by the electrification of the car sector to comply with the Danish environmental targets. The analyses are used to give policy recommendations on how to encourage modal shift away from cars to more sustainable modes of transport and to promote the deployment of electric cars. Thanks to the broad spectrum of approaches developed and tested within the scope of this research, this thesis can serve as a guide for fellow researchers interested in including a realistic representation of transport users' choice in energy system models.

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